ECONOMIC ANALYSIS OF THE INTERRELATIONSHIPS AMONG OFF-FARM WORK, PARTICIPATION IN THE CONSERVATION RESERVE PROGRAM, AND FARM PRODUCTIVITY OF FARM HOUSEHOLDS IN THE UNITED STATES

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ECONOMIC ANALYSIS OF THE INTERRELATIONSHIPS AMONG OFF-FARM WORK, PARTICIPATION IN THE CONSERVATION RESERVE PROGRAM, AND FARM PRODUCTIVITY OF FARM HOUSEHOLDS IN THE UNITED STATES

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To better understand the interaction between the farm business and the farm household, this study identifies those factors that explain participation in two major sources of non-production income of farm households: off-farm employment by the operator and the spouse and the Conservation Reserve Program (CRP). In addition, we investigate the effects of these decisions on farm efficiency and productivity.

Since there is always trade-offs between computational demands and model generalization, it is difficult to develop an empirical model that accommodates all of the interrelationships among these decisions. In this study, three specific econometric models are estimated to test if these decisions are made jointly, sequentially or independently by the farm household. Although the focus of each model differs, our empirical findings are quite robust across models.

Our results show that CRP participation depends generally on some characteristics of the farm, the farm operator, land quality, and the circumstances in the local economy. It appears that CRP acres response positively to CRP price but it decreases with the increase of low land quality. Environmental factors also play a role of CRP participation. The farm household located in areas where the EBI scores for land currently enrolled are high is more likely to participate in CRP. Our empirical

findings also support the reduction in the likelihood of CRP participation due to the increase in decoupled payments. Similar evidence is found for the decision of the farm household to engage in off-farm work. Older farmers or those who have fewer years in farming are more likely to work off the farm. In addition, the operator's education has a positive effect on the probability of participation in off-farm work.

Another unique finding of this study is the qualification of the impact on farm productivity of CRP participation and the off-farm work decision of the farm operator. It appears that participation in CRP lowers the technical efficiency and productivity, but participation in off-farm work increases technical efficiency and productivity. These results may imply that efficiency is more adversely affected when land is withdrawn from production without also withdrawn labor. However, the reverse is not true.

BIOGRAPHICAL SKETCH

Hung-Hao Chang was born in Taipei, Taiwan on June 4, 1974. He completed his high school education at the Affiliated Senior High School of National Taiwan Normal University in 1992. At the same year, he entered National Taiwan University, and received his bachelor degree from the Department of Agricultural Economics in 1996. Soon after graduation, Hung-Hao continued his education at the same department and received his Master degree in Agricultural Economics in 1998. His Master thesis won the outstanding master thesis award from the Rural Economic Society of China, Taiwan in 1999.

In 2001, after completing the military duty in Taiwan, Hung-Hao began pursuing the Ph.D. program in the Department of Applied Economics and Management at Cornell University. During his Ph.D. studies at Cornell, he worked with several faculty members, published two referred papers, and presented four conference papers at the annual meeting of the American Agricultural Economic Association. Upon conferral of his Ph.D. degree in the summer of 2006, Hung-Hao will be returning to Taiwan to pursue a career in academic research and teaching.

To my parents and Polly

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TABLE OF CONTENTS

BIBLIOGRAPHICAL SKETCH……………………………………………………..…iii

DEDICATION……………………………….………………………………..iv

ACKNOWLEDGEMENTS…………………..……………………………….v

TABLE OF CONTENTS………...………………………………………………vi

LIST OF TABLES……………....………………………………………………..x

LIST OF FIGURES……………....………………………………………..…xii

CHAPTER ONE: INTRODUCTION AND RESEARCH OBJECTIVES………..1

Introduction……...………………………………………………………......1

Research Objectives……….……...……………………………….………...3

Organization of the Study…………..…………………………………………….4

CHAPTER TWO: REVIWE OF CONSERVATION RESERVE PROGRAM AND OFF-FARM WORK………..…………….……………………...…..7

Introduction……...…………………………………………………………….7

Conservation Reserve Program.…………. ………………………………………7

Off-farm Work by Farm Households……………. …………………...…………...12

ARMS Data……………………………………………………………………...12

Distinction between Livestock and Crop Farm Households………………….13

Crop Farm Households……….………………………………………………16

Participation Rates in CRP and Off-Farm Work……………….…………….21

CHAPTER THREE: THEORETICAL BACKGROUND: AGRICULTURAL HOUSEHOLD MODEL……...………………….……………….……….24

Introduction……...………………………………………………………………24

Theoretical Framework…………..……………………………………………25

The Production Function, Risk, and Technology…..……..………….……...26

Farm Household's Maximization Problem……………………….………..……26

Comparative Static Analysis……………..…………………….…………..…33

Effects of Risk Preference and the Market Price Variability…………34

Effects of Decoupled Payments…………………...…………...…...…38

Own and Cross Price Effects…………………...…………………..41

Appendix 3A: Covariance Analysis…………..……………………..…………………44

Appendix 3B: Deriving the First Order Condition Systems…………………………45

CHAPTER FOUR: SEQUENTIAL CRP PARTICIPATION DECISIONS AND

FARM PRODUCTIVITY………………………………………………. 47

Introduction……...…………………………………………………………47

Econometric Framework…………………………………………………...48

Sequential CRP Choice Model………...……………………………..50

Second Stage Equation System…………...…………………………..52

Analysis of Farm Productivity and Technical Efficiencies…………..54

Empirical Results……...…………………………………………………...62

CRP Participation Equation…………………………………………..64

Whole or Partial CRP Farm Participation……………….……………66

Exogeneity Tests of Sequential CRP Choice Model…………………67

Second Stage Equations………..……………………………………69

Production Function and Farm Productivity…………………..……...76

Concluding Remarks……………………...………………………..84

CHAPTER FIVE: IDENTIFYING THE RELATIONSHIP BETWEEN CRP

PARTICIPATION AND THE OPERATOR'S DECISION TO WORK

OFF THE FARM……………………………………………………..……..…87

Introduction……...…………………………………………………………87

Econometric Framework…………………………………………………...89

Modeling the Joint Choice Structure…………………………………89

Modeling the Sequential Decision Choice Structure…………………95

Testing the Choice Structures and Model Selection Criterion………101

Second Stage Equations Based on the Bivariate Probit Model Framework…………….....…………………………………………...104

Technical Efficiency and Farm Productivity………………….…….108

Estimating Productivity and Efficiencies Difference between Groups…………………………….………………………………111

Empirical Results………………...…………………………………………113

Testing the Independent, Joint, and Sequential Decision Structures……………….……………………………………...125

Estimated Empirical Models………….……………………………..126

Further Justification of the Bivariate Probit Model…………………131

Second Stage Equations of Bivariate Probit Model…………………146

Estimating the Technical and Scale Efficiencies and Productivity….148

Concluding Remarks…………….…………………………………………..159

Appendix 5A: Econometric Framework of Second Stage Equations for Other Models………………………………………………….....…161

Appendix 5B: Reconsidering Normality of Bivariate Probit Model………..165

CHAPTER SIX: DETERMINING THE DECISION MAKING PROCESS BETWEEN CRP PARTICIPATION AND OFF-FARM LABOR SUPPLY OF FARM OPERATOR AND SPOUSE………………………172

Introduction……...…………………………………………………………..172

Econometric Framework Based on the Joint Decision Process…………..…173

Econometric Framework Based on the Sequential Decision Process……….177

Second Stage Analysis Based on the Joint Decision Model…….………..181

Empirical Results……………...……………………………………………185

Empirical Result of Joint Decision Process…………………………186

Determining the Sequential Decision Process………………….……...190

Test for Endogeneity of the Choice Equations……………………..…..198

Empirical Results of the Second Stage System……………………..198

Concluding Remarks……………………….……………………………..203

CHAPTER SEVEN: SUMMARY AND CONCLUSION……………………….204

Model Comparison……..………………………………..………………...207

Primary Finding of the Empirical Analysis……………………………..…..209

Some Policy Lessons……………………..………………………………211

REFERENCES…………………………………………………………………..213

LIST OF TABLES

Table 2.1: CRP Acreage Enrollment as of April 2004…………………………….…..9

Table 2.2: CRP Enrollment by State as of April 2004…………………………….….10

Table 2.3: Distinction between Different Farm Types in ARMS Data…………...….15

Table 2.4: Summary Statistics for Crop Farms…………………………………..……18

Table 2.5: Sample Distribution of CRP, Off-Farm Work Participation …………..…22

Table 2.6: Sample Distribution of CRP, OP Participations …………………….….…22

Table 2.7: Sample Distribution of CRP, SP Participations ……………………...…23

Table 2.8: Sample Distribution of OP, SP Participations ……………………………23

Table 4.1: Sequential Choice Equations ……………………………………………. 63

Table 4.2: Exogeneity Test …………………………………………………………. 69

Table 4.3: CRP Payment Equations ………………………………………………… 70

Table 4.4: CRP Acre Equations …………………………………………………….. 73

Table 4.5: Production Function Equations (Variable Returns to Scale)…………….. 77

Table 4.6: Production Function Equations (Constant Returns to Scale)…………….. 78

Table 4.7: Productivity and Efficiency Comparisons……………………………….. 80

Table 4.8: OLS Estimation of Technical Efficiency Equations……………………... 83

Table 5.1: Bivariate Probit Model Estimation …………………………………….. 114

Table 5.2: Multinomial Logit Model Estimation ………………………………….. 115

Table 5.3: Nested Multinomial Logit Model Estimation _OP Comes First..……… 118

Table 5.4: Nested Multinomial Logit Model Estimation _CRP Comes First..…….. 119

Table 5.5: Sequential Bivariate Probit Model Estimation _OP First..……………... 120

Table 5.6: Sequential Bivariate Probit Model Estimation _CRP First..…………… 122

Table 5.7: Model Selection Criterion between Models …………………………… 124

Table 5.8: IIA Test of Multinomial Logit Model ………………………………….. 125

Table 5.9: Testing for Endogeneity of OP Choice Equation ……………………… 132

Table 5.10: Estimated Acreage Payment Equations ………………………………. 134

Table 5.11: Estimated Wage Equations …………………………………………… 136

Table 5.12: Acreage Equation ……………………………………………………... 138

Table 5.13: Equations for Hours Worked off the Farm …………………………… 145

Table 5.14: Translog Production Functions by Groups …………………………… 150

Table 5.15: Comparisons of Technical Efficiency and Productivity ……………… 152

Table 5.16: OLS Estimation for Technical Efficiency Equations …….……...…… 158

Table 6.1: Trivariate Probit Model Estimation …..…………………..……………..188

Table 6.2: Sequential Choice Model _ If OP is Chosen First ……………………... 191

Table 6.3: Sequential Choice Model _ If SP is Chosen First ……………………… 194

Table 6.4: Testing for Sequential Choice Models …………………………………. 197

Table 6.5: Endogeneity Test for SP Equation ……………………………………... 198

Table 6.6: Second Stage System Estimation ………………………………………. 200

Table 6.7: Price Elasticity Estimation ……………………………………………... 202

LIST OF FIGURES

Figure 4.1: Model Structure of the CRP Sequential Choice ………………………....49

Figure 4.2: CRP Acre Response to CRP Per-Acre Price (Partial CRP Farm)………..74

Figure 4.3: CRP Acre Response to CRP Per-Acre Price (Whole CRP Farm)………..74

Figure 4.4: Distribution of the Estimated Technical Efficiency Index for Partial CRP Farm……………………………………….……………...82

Figure 4.5: Distribution of the Estimated Technical Efficiency Index for Non-CRP Participants…………………………………………….....82

Figure 5.1: Joint Decision Making Structure…………………………………………91

Figure 5.2: Sequential Decision Structure (if off-farm decision is made first)…….…96

Figure 5.3: Normalization of the Nested Multinomial Logit Model………………….99

Figure 5.4: Marginal Effect of CRP Price on CRP Acreage in Group (1, 1)………..140

Figure 5.5: Marginal Effect of CRP Price on CRP Acreage in Group (1,0)………...140

Figure 5.6: Marginal Effect of Off-Farm Wage on CRP Acreage in Group (1,1)…..141

Figure 5.7: Marginal Effects of decoupled payments on CRP Acres in Group (1,1)……………………………………..……………….144

Figure 5.8: Marginal Effect of Off-Farm Wage on Off-Farm Hours in Group (1,1)……………………………………………………….....146

Figure 5.9: Marginal Effect of Decoupled Payments on Off-Farm Hours in Group (1,1)…………………….………………………………...147

Figure 5.10: Technical Efficiency Index of Group (1,1)……………………………156

Figure 5.11: Technical Efficiency Index of Group (1,0)……………………………156

Figure 5.12: Technical Efficiency Index of Group (0,1)……………………………157

Figure 5.13: Technical Efficiency Index of Group (0,0)……………………………157

Figure 5B.1: Comparison of the predicted probability for CRP Binary Choice…….167

Figure 5B.2: Kernel Density Functions of CRP Binary Choice…………………….167

Figure 5B.3: Comparison of the Predicted Probability for Off-Farm Binary Choice……………………………………………………...168

Figure 5B.4: Comparison the density functions of off-farm Binary Choice………..168

Figure 5B.5: Bivariate Kernel Density Estimation (Graph A)………………………170

Figure 5B.6: Bivariate Kernel Density Estimation (Graph B)………………………170

Figure 5B.7: Bivariate Kernel Density Estimation (Graph C)………………………171

Figure 5B.8: Bivariate Kernel Density Estimation (Graph D)……………………....171

Figure 6.1: Trivariate Probit Model Specification…………………………………..173

Figure 6.2: Partial Sequential Decision Process (the Off-Farm Decision of the Operator is Considered Prior to Other Two Decisions)………………....178

CHAPTER ONE

INTRODUCTION AND RESEARCH OBJECTIVE

Introduction

It is now widely accepted that to meet the challenges of future agricultural policy design in the future, we must understand farm household behavior in a more complex policy context that recognizes the diverse nature of farms with respect to farm size, farm production and business organization, and environmental performance. We must also recognize the increasing interconnection between decisions made by farm businesses and farm households, and their effects on the well-being of farm families (Kuhn and Offutt 1999; Offutt, 2002).

With the conservation compliance provisions introduced in the 1985 farm bill, the importance of environmental goals was elevated to prominence along side traditional commodity policy objectives. Some farmers can receive not only commodity payments, but they can be also compensated for the environmental benefits as a by-product of farming. The number of provisions offering farmers incentives to participate in environmentally related programs has increased, with overall spending to rise by 80% under the new farm legislation—to a 10-year total of $38.6 billion. The Conservation Reserve Program (CRP), the largest program targeting land use, pays farmers $2 billion / year to remove 34 million acres from agricultural production. Through participation in particular environmental programs, some farm household labor has also has been released from agricultural production.

Another critical factor determining farm household income is the commitment by many farm households to off-farm work. When farm commodity prices are relatively low, the non-farm incomes of many farm households can exceed net farm income (Huffman 1991). Off-farm income not only supplements farm household income, it also reduces the variability of the farm household income (Mishra and Goodwin 1997). Multiple job-holdings by farm household members in the United State have become a well established strategy for the farm household to diversify household's financial position. The proportion of farm operators working over 200 or more days has risen to over 30% compared to 6% in the years following World War II (the 1994 Census of Agriculture).

To guide the direction of the agricultural policy design in the future, it is necessary to gain a better understanding of the factors affecting decisions of farm households. The primary focus of this study is to identify those factors that may affect farmers' participation in environmentally-related programs, which are increasingly incorporated into farm legislation (including those designed to retire sensitive land from production and those to promote conservation on land remaining in production). Understandably, the level of participation is also critical to enable assessment of farms' total contribution to environmental improvement. By knowing how participation differs regionally, by type of farming, and by household composition, we can also form a better foundation for predicting participation in similar state and local programs. Without this capacity, it is difficult to target payments to producers willing to retire the most environmentally sensitive lands.

It is also reasonable to assume that environmental program participation is interrelated with other programs and economic opportunities available to farm households. Among the possible alternatives, the decision of the farm households to engage in off-farm work is particularly interesting, since conservation program participation by the farm household releases land from farming, while participating in off-farm work, pulls family labor off the farms.[1] Because family labor and farm land

[1]The inter-linkage between decisions to remove land from production by placing it in conservation programs, etc. or to retain it in production is strengthened by the new farm bill through its expansion of funds for conservation on working lands.

are two critical inputs of farm production, it goes without saying that releasing these two inputs directly affects the income and input intensity on the farm, and these decisions jointly determine a farm's contribution to environmental goals, agricultural supply and agricultural productivity, as well as farm household income and wealth. As such, the second focus of this study is to understand the interrelationship between CRP participation and off-farm work of the farm household members.

Research Objectives

As stated above, the overall purpose of this research is to analyze the relationship of conservation program participation behavior and off-farm work of the farm household. Specific objectives are: 1) to identify factors related to decisions to participate in CRP; 2) to identify the extent to which off-farm labor decisions of the farm family members are related to CRP participation: are these two decisions determined jointly, sequentially or independently? 3) to identify the factors that determine the extent of CRP participations and off farm work as measured by the acreage commitment to CRP and off-farm hours worked; and 4) to quantify the effect of these participation decisions on the farm productivity and technical and scale efficiencies.

To accomplish these objectives, this study makes contributions to both theory and empirical methods. The theory generalizes the conventional agricultural household model by accounting for production and price risk, technical efficiency and decoupled payment programs. Moreover, we incorporate environmental effects into our model by recognizing the fact that the true value of the agricultural production should include the environmental benefit generated as a by-product of participation in CRP. Indeed, the optimal decisions of the farm household toward conservation program participation and off-farm jobs are affected by environmental effects, along with other economic factors.

From an empirical perspective, different modeling strategies for these two decisions are specified in order to test for the appropriate decision making process. Given the appropriate decision making process, we develop empirical methods that allow us to analyze not only the acreage and off-farm hours response, but also the effects of these decisions on farm productivity and technical and scale efficiencies. While the focus of this work is on the decisions to participate in CRP and the farm operator's participation in off-farm work, we also extend our empirical framework to the three-choice case which includes the spouse's decision work off the farm.

While it is true that to date there have been numerous attempts to model these important decisions of farm households separately, there has been much less effort to model them jointly. Further, many studies have been conducted for specific states or regions and have relied on unique data sets collected specifically for that purpose or on existing farm record data that contained the necessary information. In the past, the data needed to do a more comprehensive, national study of these joint decisions has not been available, but this roadblock has been largely removed, as the Agricultural Resource Management Survey (ARMS) data of U.S Department of Agriculture (USDA) has become available. This is the annual national survey of farm households that contains detailed information about both farm businesses and farm households. Our empirical analysis is based on 2001 ARMS data.[2]

Organization of the Study

To accomplish our study objectives, we precede in several steps. In the next chapter, we provide an historical perspective on off-farm work and the participation to CRP. Some detail on our dataset is also provided.

In Chapter 3, we provide a theoretical framework of the farm household decisions to participate in conservation programs and off-farm work. Specially, we

[2] We will introduce the details about the data used in this study in Chapter 2.

generalize the conventional farm household model by accommodating not only the production and price risk faced by the farmers, but also the technical efficiency of farm production. To help inform our empirical analysis and develop testable hypotheses, we derive the reduced forms of the optimal response in terms of acreage enrolled in conservation program and the hours worked off the farm.

We proceed with the empirical analysis in three sections (Chapters 4-6). Focusing on the CRP, given off-farm work as an exogenous choice, we analyze the participation decision and payment and acreage equations in Chapter 4 based on a multiple stage sample selection model. We also discuss the effects of CRP participation in terms of the farm technical efficiency and productivity. In this analysis, the distinction is made between those farms enrolling all or only a fraction of their farm lands in CRP. Relaxing the exogeneity assumption of off-farm work by the farm operator related to CRP participation, we focus on a two-choice sample selection model in Chapter 5. The analysis in this chapter includes two parts. The first part analyzes and compares three hypotheses of potential decision making processes of these two choices to determine if these two decisions are determined jointly, sequentially, or independently. Three conventional discrete choice models (bivariate probit, multinomial logit and nested multinomial logit) and a new proposed econometric model (sequential bivariate probit) are estimated to capture different choice decision making processes. The appropriate decision making process is consequentially determined based on several non-nested tests (Vuong test, Haussman-Wu Specification test, and Likelihood Dominance Criterion tests) to access the performance of these models. Given the appropriate decision making process, we proceed to the second stage response accounting for sample selection bias and thus identifying the effects of these two decisions on farm productivity and technical and scale efficiencies. Chapter 6 generalizes the model of the two-choice decisions by considering the spouse's choice to the off-farm work, which is also jointly determined with the participation decisions to CRP and the off-farm work decision of the farm operator. The second stage response equations are estimated and discussed in detail in this chapter.

Chapter 7 concludes with a summary and a discussion of the major conclusions to be drawn from the study.

CHAPTER TWO

REVIEW OF CONSERVATION RESERVE PROGRAM AND OFF-FARM WORK

Introduction

Since our research objective is to discuss the potential interrelationship between CRP and off-farm job participation by farm households, some background on the extent of these two decisions will help to place the empirical analysis into proper perspective. Along with this background, we also introduce the dataset used in this study, especially the frequency of participation in CRP and off-farm work by the operators and spouses of farm households.

Conservation Reserve Program

The Conservation Reserve Program (CRP) was introduced in the Farm Bill Security Act (FSA) in 1985. The program proponents sought to reduce excessive erosion, stabilize land price, and slow chronic excess agricultural production. Of these benefits, the reduction of soil erosion was the most important primary goal (Zinn 1997). Secondary goals of CRP were to protect the long-term capacity to produce food and fiber, reduce sedimentation, improve water quality, create fish and wildlife habitats, curb production of surplus commodities, and provide farm income support. Under this system, land owners, operators, and tenants could submit per-acre bids, the monetary compensation they would require in order to retire their land from production, and provide the appropriate cropping history of eligible land to county Agricultural Stabilization and Conservation Service offices. Bids less than or equal to the maximum acceptable rental rate based on a county basis were considered to be eligible. However, the maximum rental rate was calculated for each tract based on the inherent productivity of its soils and county average cropland rental rates, and the rates were never explicitly known by the bidders. If the bid is accepted, a contract to receive annual rental payment equal to the value of the submitted bid in exchange for removing their land from agricultural production is written. In addition to an annual per-acre rental payment, the farmer may also request a one-time cost share payment to partially offset the cost of conservation practices.[3]

The CRP was re-authorized and modified, especially the bidding mechanism, by the Federal Agricultural Improvement and Reform Act of 1996 (1996 FAIR Act). The maximum rental rate is established for each tract and each bid is evaluated through an environmental benefit index (EBI) with elements and scoring limits known to the bidders. The EBI is calculated according to the land characteristics to improve the environmental benefit from increasing wildlife habitat, water and air quality improvement, on farm erosion reduction, and the location of the land in a conservation priority area. As of April 2004, the total acea enrolled in CRP was approximately 34 million acres with 658 thousand active contracts (Table 2.1). There have been 28 enrollment periods and CRP acre enrollments are varied over these years. For example, the total acres enrolled in CRP of 1998 (18 million acres) is over half of the total CRP acreage enrollment (Table 2.1).

It is also true that the acres enrolled in CRP and per acre annual payments differ by state (Table 2.2). The state with the maximum CRP acre enrollment is Texas (3,967,513 acres); only 33 acres are enrolled in state of Arizona. The per-acre CRP payment is highest in Maryland ($120/acre), and only $9/acre in Arizona (Table 2.2). Nationally, average per acre-payment is $47/acre.

[3] The details of the bid system are also described in Vukina *et al.* (2003)

Table 2.1: CRP Acreage Enrollment as of April 2004

Periods	Before 1997	1997	1998	1999	2000	2001	2002	2003	2004	2005	Total
1 to 12	111,740	0	0	0	0	0	0	0	0	0	111,740
13	435,234	159,352	0	0	0	0	0	0	0	0	594,586
14	0	99,117	461,289	0	0	0	0	0	0	0	560,406
15	0	0	16,178,980	356,167	0	0	0	0	0	0	16,535,147
16	0	0	1,775,297	4,078,831	0	0	0	0	0	0	5,854,128
17	0	0	113,044	103,637	0	0	0	0	0	0	216,681
18	0	0	0	0	4,750,726	0	0	0	0	0	4,750,726
19	0	0	0	135,137	131,086	0	0	0	0	0	266,223
20	0	0	0	0	0	2,249,912	0	0	0	0	2,249,912
21	0	0	0	0	106,071	12,648	0	0	0	0	118,719
22	0	0	0	0	33,387	171,443	0	0	0	0	204,830
23	0	0	0	0	0	220,668	247,174	0	0	0	467,842
24	0	0	0	0	0	0	289,461	150,186	0	0	439,647
25	0	0	0	0	0	0	0	198,049	53,203	0	251,252
26	0	0	0	0	0	0	0	0	1,664,077	141843	1,805,920
27	0	0	0	0	0	0	0	11,448	168,168	0	179,616
28	0	0	0	0	0	0	0	0	114,101	2665	116,766
Total	546,974	258,469	18,528,610	4,673,772	5,021,270	2,654,671	536,635	359,683	1,999,549	144,508	34,724,144

** Summarized from FSA (2004)*

Table 2.2: CRP Enrollment by State as of April 2004

State	Number of Contracts	Acres (ha)	Payment ($/Acre)
ALABAMA	10,157	484,466	45
ALASKA	64	29,524	33
ARIZONA	1	33	9
ARKANSAS	3,931	189,936	48
CALIFORNIA	520	147,136	31
COLORADO	12,499	2,289,555	31
CONNECTICUT	26	318	66
DELAWARE	679	7,473	100
FLORIDA	1,945	88,207	37
GEORGIA	8,261	308,832	39
HAWAII	1	19	93
IDAHO	5,418	789,006	38
ILLINOIS	64,403	996,559	101
INDIANA	28,138	282,931	88
IOWA	90,745	1,888,571	103
KANSAS	41,372	2,869,686	38
KENTUCKY	13,648	333,825	73
LOUISIANA	3,415	238,108	46
MAINE	844	23,359	50
MARYLAND	6,125	84,253	120
MASSACHUSETTS	17	121	103
MICHIGAN	14,312	258,200	71
MINNESOTA	54,296	1,762,824	58
MISSISSIPPI	19,749	931,264	41
MISSOURI	32,884	1,553,935	66
MONTANA	17,836	3,423,007	33
NEBRASKA	24,794	1,191,164	54
NEVADA	1	151	16
NEW HAMPSHIRE	17	196	52
NEW JERSEY	136	2,406	49
NEW MEXICO	2,621	596,093	31
NEW YORK	2,411	58,381	43
NORTH CAROLINA	7,146	121,497	59

Table 2.2: (Continued)

State	Number of Contracts	Acres (ha)	Payment ($/Acre)
NORTH DAKOTA	35,143	3,356,038	33
OHIO	22,869	275,269	83
OKLAHOMA	8,855	1,035,874	32
OREGON	3,023	495,781	48
PENNSYLVANIA	7,116	151,632	76
PUERTO RICO	20	671	89
SOUTH CAROLINA	8,677	213,420	35
SOUTH DAKOTA	24,394	1,456,279	40
TENNESSEE	8,093	273,102	58
TEXAS	24,068	3,967,513	35
UTAH	1,037	200,279	30
VERMONT	117	1,390	76
VIRGINIA	4,163	62,041	52
WASHINGTON	10,731	1,379,378	52
WEST VIRGINIA	152	2,292	59
WISCONSIN	30,321	621,726	68
WYOMING	1,098	280,419	27
U.S	658,289	34,724,144	47

** Summarized from FSA (2004)*

Off-Farm Work by Farm Households

Part time and multiple job holdings among the farm household members is not new, and has been evident for United States farms for over fifty years. Many farm households combine farming with a variety of other pursuits, since off farm work by farm operators and their spouses has traditionally been viewed as an action necessary to save the farm by providing resources to pay farm bills or to repay debt (Ahearn and Lee 1991). In past years, off-farm employment was also considered temporary and as a income supplement (Mishra, *et al.* 2002). Due to the low price and income elasticities for agricultural products and technological advancements during the past three decades, supplies of many agricultural commodities have grown more rapidly than the demand, in many cases leading to low farm incomes. At the same time, the growing real wage rate from the off-farm sector provided incentives for the farm household members to take jobs off the farm to compensate low farm incomes. As such, the long term trend for participating on the off-farm job of the farm household operator increased by 24% from 1979-1999 and 65% for his or her spouse (Mishra, *et al.* 2002).

Traditionally, married women were considered to specialize on the household production and men to specialize on farm production. However, with increasing in the wage rate of the off-farm sector, the spouse is more likely to work in the paid off-farm market, thus the household tasks may now be shared between spouses. The U.S historical data supports this long term trend. To date, almost 70% of farm households have either the operator, spouse, or both engaged in off-farm employment (Mishra, *et al*. 2002).

ARMS Data

The primary farm household data used in this study are from the 2001 Agricultural Resource Management Survey (ARMS), which is conducted by the

National Agricultural Statistics Service of the United State of Agriculture (USDA). ARMS data are USDA's primary vehicle for collecting and disseminating data on a wide range issues about resource use and farm financial conditions. The relationship between agricultural production, resources, and the environment is reflected in this dataset. Moreover, the data record program participation decisions and related payments received by the farm households. Importantly, ARMS data contain the information on the farm household relative to several environmental program participations, including CRP, CREP, and EQIP, one of which is the primary focus of this study. Since the objective of this paper is to understand the response of participation in CRP and the off-farm labor market participation of the farm household, we limit our sample to the agricultural farm household farms.[4]

Distinction between Livestock and Crop Farm Households

Since crop and livestock farms produce different agricultural commodities, it is likely that these two different types of farm households allocate their household resources to available programs in different ways. In addition, this distinction is also important because one of our objectives is to investigate the effects of CRP participation and off-farm work on farm productivity. To do this, we focus on crop farms in order to avoid the difficulty in accounting for major differences in farm technology between crop and livestock operations. Furthermore, two different types of CRP participants have been recognized in the literature: "whole" CRP farms and "partial" CRP farms (Sullivan, *et al.* (2004)). The whole CRP participants are those who enroll all or most cropland in CRP and have no sales of agricultural commodities, while the partial CRP farms are those who only enroll part of the cropland in CRP.[5] To place these groups of farm into perspective with the entire sample of farms in the

[4] Version 1, phased III of ARMS data in the year 2001 is used in this study.
[5] We distinguish and analyze the decision making process of these two types of farms in more detail in Chapter 4.

ARMS data, we compare them in terms of several important variables in Table 2.3.

To begin, we focus on the comparison between livestock and crop farms. The proportions of these two types of farms are 52% and 48%, respectively, and the operator and farm characteristics of these two groups are similar. However, more operators of livestock farms commit to off-farm work than for crop farms (66% vs 56%). A slightly smaller fraction of spouses on livestock farm households works off the farm than for crop farm households (49% vs 52%). More important for our purpose is the fact that only 2% of livestock farms are in CRP; this is much lower than the participation rate of crop farms (23%). The average acres enrolled in CRP is also quite different (4 vs 163 acres).

In comparing the CRP participants and the non-CRP participants of the crop farms, we find that the CRP participants are slightly older on average and have more farming experience. However, CRP participants are also those with larger farms on average. The operated areas for CRP participants and non-CRP participants average 607 and 346, respectively. As for the commitment to the off-farm work, our data show similarity for both farm operators and spouses between these two groups.

If we further limit our attention to the CRP participants of the crop farms, we find that the small farms are more likely to enroll the entire land into CRP, and whole farm participants are also older.

Table 2.3: Distinction Between Different Farm Types in ARMS Data

	Farm Type						
	All	Livestock	Crop				
			All	CRP=0	CRP=1		
Variable					All	Partial	Whole
Sample Proportion	1	0.52	0.48	--	--	--	--
Operator Age	54	53	55	53	60	57	62
Operator Experience	23	21	25	25	27	30	25
Operating Acres	411	415	407	346	607	1,035	299
Own	220	226	211	155	396	471	342
Rent In	207	198	219	205	264	591	28
Rent Out	15	9	24	14	53	28	71
Crop Sale	25,179	2,992	54,883	58,642	42,434	101,502	0
Livestock Sale	24,825	39,259	5,501	5,335	6,053	14,083	285
Risk	4.4	4.3	4.4	4.7	3.7	5.1	2.6
Low Land Quality	0.27	0.30	0.23	0.25	0.18	0.14	0.22
CRP	0.12	0.02	0.23	--	--	0.10	0.13
OP	0.62	0.66	0.56	0.56	0.55	0.52	0.58
SP	0.50	0.49	0.52	0.52	0.53	0.55	0.51
CRP Acres	18	4	163	--	163	151	171
CRP Acres/Crop Land	0.07	0.02	0.12	--	0.59	0.25	0.90
CRP Acres/Operating Land	0.05	0.01	0.11	--	0.46	0.18	0.65
CRP Per Acre Payment	62	51	65	--	65	77	56
Hour_OP	1,209	1,304	1,080	1,105	995	744	1,181
Hour_SP	868	847	968	920	825	885	782
Wage_OP	28	27	29	31	23	29	18
Wage_SP	17	19	15	16	15	15	15

* *All variables are summarized from ARMS 2001, and weighted by full sample weights*

Crop Farm Households

Since the objective of this study is to understand the participation decisions in CRP and off-farm work of farm households, we limit our attention to the sample of farm households, and we exclude some large corporate operations, etc. We also limit our attention to farms classified as crop farms because of our interest in examining the effect of CRP participation and off-farm work on farm productivity. As always in a data set of this magnitude and complexity, a few observations were eliminated because of the erroneous coding of information or due to missing data when some respondents refused to answer particular questions. The final sample count is 2,223.[6]

Although the ARMS data contain valuable information of the farm household, they do not provide any information of local area characteristics and the physical conditions related to the environment, which are likely to be factors in determining off-farm work and the CRP participation decisions of the farm household. As such, we utilize some auxiliary data from other sources. The economic characteristics of the local areas are merged into our ARMS dataset based on the county level from the Bureau of Economic Analysis income files in 2000, the Bureau of Economic Analysis employment files in 2000, the Bureau of Labor Statistics, and the 1990 Census of Population, STF-3 file.[7]

Since one policy goal of CRP is to promote the environmental benefits to society, physical (environmental) conditions are likely to play a special role in the participation decision of the farm household. Therefore, three variables representing the different land quality at the county level in which the farm is located are specified.

[6] In most of the content, the sample size we use is 2,223. However, we lose some sample by specifying the spouse's characteristics in the three choices analysis (Chapter 6). In that Chapter, the same size is 2,102. Since the sample statistics of these two different samples are very close, we only list the data information based on sample size 2,223 in Table 2.4.
[7] The same local economy dataset is also used by El-Osta, Mishra, and Ahearn (2004). We express appreciation to them for sharing the data.

We define land quality by accounting for the growing season length and the land capability classification index. The data on growing season length, drawn from the global economic model, are developed to reflect long-run agricultural and environmental sustainability (Darwin and Ingram (2004)). In their paper, the growing season variable is the estimate of the length of the rain-fed growing season. The land capability classification index, defined by Natural Resources Conservation Survey (NRCS), is used for developing the erodible cropland index. This index is calculated based on quantifiable factors in the universal soil loss equation.[8]

Another critical factor that may determine the CRP participation is the Environmental Benefits Index (EBI), which is designed by Farm Service Agency (FSA) and NRCS based on each ERS region. The EBI score assigns a weight for each category of environmental benefit to each offered parcel. There is a handbook that lists specific details on how points are to be assigned for each conservation practice and land characteristic (USDA 1997).[9] The index, along with a cost factor, is critical in determining the bids that can he accepted for CRP enrollment. Due to the unavailability of the accurate information about EBI assigned to each farm household from the ARMS data, we utilize the EBI index from Jaroszewski (2000) to document average EBI scores for land currently enrolled in CRP. Descriptions of the variables included in the analysis are in Table 2.4.

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[8] We express our appreciation to Roger Claassen for making the data available. The variables are defined as: LQH96 = "high" land quality = GS*(LCC1+LCC2); LQM96 = "medium" land quality = GS*(LCC3+LCC4); and LQL96 = "low land quality = GS*(LCC5+LCC6+LCC7+LCC8), where LCCi = percentage of land in the county that is in soil capability class i, and GS = the ratio of the mean rain-fed season to the mean irrigated season.

[9] The components of EBI are: Wildlife habitat, Water quality Benefit from water erosion reduce, Wind reduction, Long-term benefit from of Cover beyond the contract period, Air quality benefit, Conservation propriety areas enrollment, and Cost factor.

Table 2.4: Summary Statistics for Crop Farms

Variable Names	Variable Definitions	Mean	Std.
Program Participation			
CRP_CREP	If the household enroll in CRP or CREP (=1); otherwise (=0)	0.23	0.42
WHOLE_CRP	If the household enroll in CRP or CREP as whole-farm(=1); otherwise (=0)	0.13	0.34
PARTIAL_CRP	If the household enroll in CRP or CREP as partial-farm(=1); otherwise (=0)	0.10	0.30
OP	If the operator works off farm (=1); otherwise (=0)	0.56	0.50
SP	If the spouse is work off farm (=1); otherwise (=0)	0.53	0.50
Price and Level of Participations			
P_CRP_C	Per acre CRP payment	64.70	0.71
WAGE_OP	Operator's off-farm job wage	29.00	0.74
WAGE_SP	Spouse's off-farm job wage	15.50	1.36
A_CRP_C	Acre enrollment in CRP of the agricultural household	162	293
HOUR_OP	Annual working hours on off farm job of the operator	1,080	842
HOUR_SP	Annual working hours on off farm job of the spouse	968	813
Environmental Characteristics			
EQIP	If participate in EQIP (=1), otherwise(=0)	0.00	0.05
EBI	Environmental benefit index	61.67	3.85
LQH_96	Index of high quality land of 1996	0.33	0.25
LQM_96	Index of medium quality land of 1996	0.29	0.15
LQL_96	Index of low quality land of 1996	0.23	0.19
Operator Characteristics			
OP_TECH	If the the off-farm job of the operator is works as a technician(=1); otherwise (=0)	0.12	0.32
OP_JOBR3	If the operator works off-farm for health insurance or benefit from federal government (=1); otherwise(=0)	0.03	0.18
OP_RET	If the operator is retired (=1); otherwise(=0)	0.11	0.31
OP_ED_C	Education level of the operator (years)	13.08	2.45
OP_EDSQ	Square terms of education level of the operator (year)	177	65
OP_AGE	Age of the operator	54.57	13.71
OP_AGESQ	square term of operator age	3.17	1.52
OP_EXP	Years of the operator working on farm job	25.50	63.00
OP_EXPSQ	Square of years that the operator works on farming job	4,618	123,835
OP_EXP_F	Operator's experience for the off-farm job	7.34	10.33
RAISE_OP	If the operator was raised on the farm (=1); otherwise (=0)	0.79	0.41
RISK	Risk preference rating of the operator; =0 if risk averse, 10 if risk loving	4.43	2.46

Table 2.4: (Continued)

Variable Names	Variable Definitions	Mean	Std.
Spouse Characteristics			
SP_AGE	Age of the spouse	52.67	13.38
SP_AGESQ	Square term of spouse age	2,953	1,425
SP_ED_C	Education level of the spouse (years)	13.35	2.09
RAISE_SP	If the spouse was raised on the farm (=1); otherwise (=0)	0.53	0.50
SP_HMAK	If the spouse is a home maker (=1); otherwise (=0)	0.25	0.43
Farm and Household Characteristics			
NETWORT1	Household networth value divided by 100,000	4.61	15.70
DEBT_RAT	Ratio of total debts to total assets	0.20	2.34
H_SIZE	Number of household members	2.74	1.26
H_SIZE06	Number of household members under 6 years old	0.13	0.47
H_SIZE13	Number of household members under 13 years old	0.24	0.65
CROP17	If the cash grain farm, (=1),otherwise (=0)	0.71	0.46
CROP456	If vegetable, fruit, or nursery farm, (=1),otherwise (=0)	0.21	0.41
AMTA_A	Per acre AMTA (Agricultural Market Transition Act) payment	5.42	12.57
LDP_A	Per acre LDP (Loan Deficiency Payment) payment	8.25	18.63
CROPSIZ1	Operating acreage for cropland divided by 1,000	0.32	0.68
TENANCY	Self-own acreage devided by total acreage	0.95	2.08
DIST_OP	Distance from home to the off-farm job	9.88	93.10
AGDIST	if the operator participates in other local agricultural preservation program (=1); otherwise (=0)	0.05	0.22
MILES	Miles from home to nearest town with population of at least 10,000	22.82	20.82
Location and Local Economic Condition			
UNEMP	LMA's unemployment rate (%), lagged one year	4.18	1.85
URBAN	Percent of labor market area's population living in urban areas, based on 1990 census of population	56.06	22.17
MANUF	LMA's employment in manufacturing (%), lagged one year	13.84	6.90
TRADE	LMA's employment in wholesale and retail trade (%), lagged one year	20.32	2.35
AGRIN	LMA's income from agriculture (%), lagged one year	4.21	6.82
SERV	LMA's employment in service (%), lagged one year	26.17	4.97
REGN1	If the household is located in ERS region 1(Heartland) (=1); otherwise (=0)	0.28	0.45
REGN2	If the household is located in ERS region 2 (Northern Crescent) (=1); otherwise (=0)	0.16	0.37
REGN3	If the household is located in ERS region 3 (Northern Great Plains) (=1); otherwise (=0)	0.08	0.27
REGN567	If ERS region 5 (Eastern Uplands), 6 (Southern Seaboard), 7 (Fruitful Rim) (=1); otherwise (=0)	0.29	0.45
REGN9	If the household is located in ERS region 9 (Mississippi Portal) (=1); otherwise (=0)	0.05	0.22

Table 2.4: (Continued)

Variable Names	Variable Definitions	Mean	Std.
Production Performance			
OUTPUT	Crop and livestock sale ($1,000)	60	219
HOUR	Hours working on the farm by operator and spouse	1,694	1,401
LC_C	Operating cost, including livestock expense,crop expense,energy expense ($)	36,267	98,346
LAND	Operated acres (ha)	407	923
CAPITAL	Value of total non-current assets minus the principal operator dwelling ($1,000)	466	1,600
LABOR	Hired labor cost ($)	9,823	61,908

* Note: All variables are weighted by full sample weight

Participation Rates in CRP and Off Farm Work

For purposes of this analysis, some of the most critical pieces of sample information are the frequencies of CRP participation, off-farm labor supply of the operator and spouse of the farm household. We summarize these frequencies for these three decisions in Table 2.5.[10]

If we consider each of these three choices as a binary choice, the data contain eight different combinations of participation possibilities. Table 2.5 lists the sample frequency of these eight possibilities. Among all of the eight groups, the participation rates vary between groups. The highest rate is 26.4%, for both of the groups that operator and spouse participate in off-farm work, and the lowest rate is 2.8%, for those who participate in CRP and only the operator works off the farm.[11] More detail on each pair of decisions is listed in Table 2.6-2.8.

[10] In subsequent analysis, we pay special attention to different types of CRP participation. Two different CRP participation behaviors have been mentioned in the literature (Sullivan *et al.* (2004). The first class is referred to as the whole CRP farms, for those participants that enroll all land in CRP and no longer engage in agricultural production. The other class of participant is referred to as the partial CRP farm, for those who not only enroll in CRP but also retain some land in production. Our data show that the whole and partial CRP farms participation rates are 13% and 10%, respectively, of the overall 23% CRP participants (from Table 2.3).
[11] In order to represent the population of the nation, we weight the observations with full sample weight. As such, the participation rates reported here can be regarded as the national participation.

Table 2.5: Sample Distribution of CRP, Off-Farm Work Particiaption

Groups	CRP	OP	SP	Frequency	*%*
(1,1,1)	1	1	1	200	*9.51*
(1,1,0)	1	1	0	59	*2.81*
(1,0,1)	1	0	1	74	*3.52*
(1,0,0)	1	0	0	142	*6.76*
(0,1,1)	0	1	1	555	*26.40*
(0,1,0)	0	1	0	285	*13.56*
(0,0,1)	0	0	1	366	*17.41*
(0,0,0)	0	0	0	421	*20.03*
Total				2,102	*100*

*** weighted with full sample weights*

Table 2.6: Sample Distribution of CRP, OP Participations

	OP		
CRP	0	1	Total
0	787	840	1627
%	*37.44*	*39.96*	*77.40*
1	216	259	475
%	*10.28*	*12.32*	*22.60*
Total	1003	1099	2102
%	*47.72*	*52.28*	

*** weighted with full sample weights*

Table 2.7: Sample Distribution of CRP, SP Participations

	SP		
CRP	0	1	Total
0	706	920	1626
%	*33.59*	*43.77*	*77.35*
1	200	276	476
%	*9.51*	*13.13*	*22.65*
Total	906	1196	2102
%	*43.10*	*56.90*	

*** weighted with full sample weights*

Table 2.8: Sample Distribution of OP, SP Participations

	SP		
OP	0	1	Total
0	563	441	1004
%	*26.78*	*20.98*	*47.76*
1	343	755	1098
%	*16.32*	*35.92*	*52.24*
Total	906	1196	2102
%	*43.10*	*56.90*	

*** weighted with full sample weights*

CHAPTER THREE

THEORETICAL BACKGROUND: AGRICULTURAL HOUSEHOLD MODEL

Introduction

For at least four decades, economists have recognized explicitly that the household not only buys market goods, but also combines its time to undertake activities whose outputs contribute directly to utility maximization. This framework explores the interests of economists in the time allocation within the family, since the households are not only buyers, but also the producers. The seminal paper by Gary Becker (1965) laid the economic foundation for a robust literature addressing labor force participation decisions within the context of the household framework.[12] Becker's model has been widely applied to the study of family bargaining behavior, and the marriage issue which are interesting topics in the field of family economics (e.g. Parkman 2004).

Due to its relative simplicity and the diversity of issues it can address, Becker's framework has also been applied widely by development economists, who expanded the model for the study of diverse livelihood strategies of subsistence farms in the less or developed countries (Singh *et al.* 1986). When the household model is applied to the field of agriculture, it is more complex due to the special features of agricultural production.[13] First, the farm household may be involved in several activities off the farm in order to sustain the farm household income. The off-farm job participation rates in developing countries are documented by Abdulai and Delgado (1999). In the US, 55% of farms in the US Agricultural Census Survey of year 1986 reported off-farm work earning in excess of farm income, and income from off-farm work accounts

[12] Pollak (2003) has a comprehensive review of Becker's contribution and influence to the family economics literature. In this paper, he also discussed some potential drawback of the auxiliary assumptions imposed by Becker's theoretical model.

[13] Thirty years earlier, Heady (1952) underscores the complexity as well.

for 46% of the total income for farm household in the same year (Ahearn and Lee (1991)). Previous studies have also indicated that the long time trend for participating in off-farm work by farm household operators increased by 24% since 1979 (Huffman (1991); Mishra, *et al.* 2002). Second, agricultural authorities also implement agricultural commodities programs in order to stabilize agricultural markets. Thus, when considering farm households, it is also important to consider participation in traditional agricultural commodity programs (such as price support) or other programs attempting to secure the farm income (decoupled payments). Opportunities to participate in these programs complicate the structure of the model.

Although previous studies have included other special features of agricultural production into a household model framework, they have not considered some important issues mentioned above.[14] This chapter provides a description of the optimal farm household labor, both on farm and off-farm labor supply decisions, as well as the land allocation decisions given opportunities to participate in the conservation reserve program and other government programs. We also consider the effects of risks on agricultural production, as well as the effects on technical efficiency or productivity.

Theoretical Framework

To focus on the essence of these combined choices (CRP and/or off farm work participation), we assume that all decisions are made by one member of the farm household—the farm operator.[15] There are fixed endowments of time ($\bar{E}$) and of farmland ($\bar{A}$). Time is allocated to leisure (l), farm production (L), and off-farm work (L_m). The household receives income from several sources: agricultural product sales,

[14] One of the special features widely included in to the agricultural household model is the agricultural production risk. Fabella (1989) and Kanwar (1999) analyzed the optimal labor supply response in several versions of risk analysis. Dawson (1988) discussed the optimal labor supply decisions of the farm family, including operator, spouse and other family members. Saha (1995) derive the compensated optimal response under uncertainty in farm household models.

[15] While the presence of a spouse and children conditions the farmer's decisions, we abstract from complications associated with work on and off the farm by family members.

off-farm work at an off-farm wage (w), CRP payment per acre (P_e), and decoupled farm payments, (M). Land is allocated between crop production (A), and CRP (A_e). Finally, we assume that utility depends not only on farm household consumption (x) and leisure (l), but also on the improvement in environmental quality (e) generated by land committed to CRP.

The Production Function, Risk, and Technology

Agricultural production, y, depends on land and labor, where y = F (L, A) is a well-behaved concave production function. We assume that the commodity price, *P*, is random, $P = \overline{P} + \eta$, where $\overline{P}$ is the expected price and the random error follows an arbitrary distribution with mean zero and variance σ_η^2 ($\eta \sim (0, \sigma_\eta^2)$). To reflect output risk, we use the general form proposed by Just and Pope (1979). The efficiency of the technology is also incorporated explicitly. The production function is: $F(L, A) = f(L, A) + g(L, A)\varepsilon - h(L, A)u$. The error associated with output risk, ε, is assumed to follow an arbitrary distribution of $\varepsilon \sim i.i.d(0, \sigma_\varepsilon^2)$. An input is regarded as risk increasing (decreasing) if g' (.) is positive (negative). Production efficiency is reflected in $h(L, A)u$, where $u \sim i.i.d(\overline{u}, \sigma_u^2)$ is the random noise on a stochastic production frontier function. The efficiency of technology, T.E, is given by:

$$T.E = \frac{E(F(L, A))}{E(F(L, A))|_{u=0}} = \frac{f(L, A) - h * \overline{u}}{f(L, A)} \leq 1;$$

$f(L,A)$ is mean production and $h * \overline{u}$ measures efficiency for the mean level of inputs.

Farm Household's Maximization Problem

Given this specification of farm production technology, the agricultural household maximizes expected utility, subject to a full income constraint, a time constraint, and an acreage constraint.

The maximization problem of the agricultural household can be written as:

(3.1) $\underset{x,l,A_e}{Max} = E\{U[x,l,e(A_e)]\}$

s.t.

(3.2) $x = (\overline{P} + \eta)F(L, A) + wL_m + P_e A_e + M$

(3.3) $\overline{E} = L + L_m + l$

(3.4) $\overline{A} = A_e + A$.

We can eliminate l and x by substituting equations (3.2 through 3.4) into equation (3.1). The choice variables are land in CRP (A_e), labor in off-farm work (L_m), and labor used for agricultural production (L). The maximization problem can be rewritten as:

(3.5)

$$\underset{A_e,L_m,L}{Max} = EU\{[(\overline{P}+\eta)(f(L,\overline{A}-A_e)+g(L,\overline{A}-A_e)\varepsilon - h(L,\overline{A}-A_e)u)+wL_m+P_eA_e+M],$$
$$[\overline{E}-L-L_m],e(A_e)]\}.$$

The first-order necessary conditions for interior solutions are:[1]

(3.6) $\dfrac{\partial EU}{\partial A_e} = E\{-U_x[(\overline{P}+\eta)(f_A + g_A\varepsilon - h_A u) - p_e] + U_e e_{A_e}\} = 0$

(3.7) $\dfrac{\partial EU}{\partial L_m} = E\{U_x w - U_l\} = wE(U_x) - E(U_l) = 0$

(3.8) $\dfrac{\partial EU}{\partial L} = E\{U_x[(\overline{P}+\eta)(f_L + g_L\varepsilon - h_L u)] - U_l\} = 0,$

where U_i is the first-order derivative of the utility function with respect to argument i. The optimal levels of A_e, L_m, and L for the agricultural household are given by the simultaneous solution of equations (3.6), (3.7), and (3.8).

[1] In order to make the analysis tractable, the marginal utility of leisure and CRP land are assumed to be independent. That is: $U_{AeL}=U_{LAe}=0$ (Fabella 1989; Kanwar, 1999).

From equation (3.7), labor is allocated to off-farm work until the ratio of the expected marginal utility of leisure to the expected marginal utility of consumption is equal to the off-farm wage (w).

To interpret the other first-order conditions, it is necessary to take the expectations of both equations (3.6) and (3.8). In so doing, the first term of equation (3.6) can be expanded into:

$$(3.9)\quad \begin{aligned}&\overline{P}[f_A E(U_x) + g_A E(U_x\varepsilon) - h_A E(U_x u)] + [f_A E(U_x\eta) + g_A E(U_x\varepsilon\eta) - h_A E(U_x u\eta)]\\ &+ P_e E(U_x).\end{aligned}$$

By taking expectations and applying the appropriate approximation (Bohrnstedt and Goldberger (1969)), then substituting these expressions for expected values and covariances into equations (3.6) and (3.8), the first-order necessary conditions are now:

$$(3.10)\quad \frac{\partial EU}{\partial A_e} = -\overline{P}[(f_A - h_A\overline{u})E(U_x) + g_A Cov(U_x,\varepsilon) - h_A Cov(U_x,u)]$$

$$- Cov(U_x,\eta) f_A - E(U_x)[g_A Cov(\eta\varepsilon) - h_A Cov(\eta u)] + P_e E(U_x) + E(U_e)e_{A_e} = 0$$

$$(3.11)\quad \frac{\partial EU}{\partial L} = \overline{P}[(f_L - h_L\overline{u})E(U_x) + g_L Cov(U_x,\varepsilon) - h_L Cov(U_x,u)]$$

$$+ Cov(U_x,\eta) f_L + E(U_x)[g_L Cov(\eta\varepsilon) - h_L Cov(\eta u)] - E(U_l) = 0$$

The optimal levels of acre enrollment in CRP, equation (3.10), and labor for production, equation (3.11), are more complex compared with standard farm-household production models, because the optimal decisions depend on the covariance of the expected marginal utility with each source of risk, the covariances of the random variables of different sources of risk sources, the expected marginal utility, and risk characteristics of farm inputs.

To understand the economic intuition, we examine the set of first-order conditions systematically by isolating four separate cases: 1) price risk only; 2) yield risk only; 3) technology efficiency only; and 4) price and yield risk jointly. In so doing, the interpretation of equations (3.7) remains the same. We repeat it for completeness, but focus on the interpretations of the simplified versions of equations (3.10) and (3.11).

<u>Case 1: Price Risk Only</u>

If only price risk is considered, the first-order conditions simplify to:

$$(3.12)\quad \frac{\partial EU}{\partial A_e} = P_e E(U_x) - \overline{P} f_A E(U_x) - Cov(U_x, \eta) f_A + E(U_e) e_{A_e} = 0$$

$$(3.13)\quad \frac{\partial EU}{\partial L_m} = wE(U_x) - E(U_l) = 0$$

$$(3.14)\quad \frac{\partial EU}{\partial L} = \overline{P} f_L E(U_x) + Cov(U_x, \eta) f_L - E(U_l) = 0\,.$$

The first term in equation (3.12) is the CRP payment multiplied by the expected marginal utility of consumption. This, combined with the fourth term, the marginal utility of environmental quality multiplied by the marginal contribution of CRP land to environmental quality, is the marginal benefit to the household of land allocated to CRP. The second term is the revenue foregone from allocating land to CRP rather than to production, again multiplied by expected marginal utility of consumption, while the third term is the covariance between price risk and marginal utility of consumption. At the optimum, the marginal benefit of land allocated to CRP is equated to the opportunity cost of land in agricultural production, adjusted for the covariance between price risk and the marginal utility of consumption $Cov\ (U_x, \eta)$.[16] Thus, assuming concave utility and production functions, when compared with a

[16] The sign of this term depends on the risk attitude of the agricultural decision makers. As seen in Appendix 3A, if the decision maker is risk averse, this term is negative; and if the decision maker is risk loving, this term is positive.

farmer who is risk neutral, a risk averse farmer will choose to increase the enrollment in CRP. Similarly, the optimal enrollment in CRP for a risk-loving farmer would be lower than for risk neutrality.

Similar arguments can be applied to equation (3.14). Under risk neutrality, the farmer would equate the marginal utility of leisure to the marginal utility of consumption multiplied by the expected marginal value product of labor. If the farmer is risk averse, the equilibrium expected marginal utility of leisure must fall (amount of leisure must increase relative to the risk neutral situation), suggesting that labor allocated to agricultural production must fall.

<u>Case 2: Yield Risk Only</u>

When only yield risk is considered in the agricultural household model, the system of first-order necessary conditions (3.6, 3.7, and 3.8) can be simplified as:

$$(3.15)\quad \frac{\partial EU}{\partial A_e} = -\overline{P}[f_A E(U_x) + g_A Cov(U_x,\varepsilon)] + P_e E(U_x) + E(U_e)e_{A_e} = 0$$

$$(3.16)\quad \frac{\partial EU}{\partial L_m} = wE(U_x) - E(U_l) = 0$$

$$(3.17)\quad \frac{\partial EU}{\partial L} = \overline{P}[f_L E(U_x) + g_L Cov(U_x,\varepsilon)] - E(U_l) = 0\,.$$

The economic interpretation of equation (3.15) is similar to that of the corresponding equation in Case 1. At the optimum, the expected marginal benefit of land allocated to CRP is equated to the expected opportunity cost of land in agricultural production adjusted again for the riskiness of agricultural return. The difference is due to the fact that risk in return stems from risk in yield rather than price risk. As above, we know that $Cov\ (U_x,\varepsilon) < 0$ for a risk averse farmer, but, we don't know *a priori* that a risk averse farmer will place more in CRP than a risk neutral farmer. The answer depends on the sign of g_A. If land is a risk increasing input (e.g. $g_A > 0$), the optimal acreage in CRP is larger than for the risk neutral farmer. However, acreage in CRP will be smaller than for the risk neutral individual if land is a risk decreasing input (e.g. $g_A < 0$). From equation (3.17), we know that if labor is risk increasing, a risk averse farmer will allocate less labor to agricultural production than will a risk neutral farmer. The reverse is true if labor is risk decreasing.

<u>Case 3: Technology Efficiency Only</u>

In this case, the first-order conditions are:

$$(3.18)\quad \frac{\partial EU}{\partial A_e} = -\overline{P}[(f_A - h_A\overline{u})E(U_x) - h_A Cov(U_x, u)] + P_e E(U_x) + E(U_e)e_{A_e} = 0$$

$$(3.19)\quad \frac{\partial EU}{\partial L_m} = wE(U_x) - E(U_l) = 0$$

$$(3.20)\quad \frac{\partial EU}{\partial L} = \overline{P}[(f_L - h_L\overline{u})E(U_x) + h_L Cov(U_x, u)] - E(U_l) = 0\,.$$

By construction, technology inefficiency affects the first-order conditions in a way similar to that of output risk. Using an argument similar to that for the case of output risk, we know that $Cov(U_x,u) > 0$. Further, inputs can now be either efficiency decreasing, the marginal effect (h_A) > 0, or efficiency improving, the marginal effect (h_A) < 0. Thus, relative to the case where the efficiency of the technology is known, the optimal land enrolled in CRP will increase if land in agricultural production is efficiency decreasing. At the margin, the farmer can avoid the cost of inefficiency in production by allocating less land to production and receive payment for enrolling land in CRP. From equation (3.20), one can develop similar conclusions about labor allocated to farm production relative to the case where technical efficiency is known.

Case 4: Price and Yield Risk

When output risk and price risk are considered jointly in the agricultural household model, the first-order necessary conditions can be simplified as:

$$(3.21)\quad \frac{\partial EU}{\partial A_e} = -\overline{P}[f_A E(U_x) + g_A Cov(U_x, \varepsilon)] - Cov(U_x, \eta) f_A - E(U_x) Cov(\eta\varepsilon) g_A$$

$$+ P_e E(U_x) + E(U_e) e_{A_e} = 0$$

$$(3.22)\quad \frac{\partial EU}{\partial L_m} = wE(U_x) - E(U_l) = 0$$

$$(3.23)\quad \frac{\partial EU}{\partial L} = \overline{P}[f_L E(U_x) + g_L Cov(U_x, \varepsilon)] + Cov(U_x, \eta) f_L + E(U_x) Cov(\eta\varepsilon) g_L$$

$$- E(U_l) = 0$$

The optimality conditions for the levels of CRP area, equation (3.21), and labor for production, equation (3.23), are more complex, compared with standard farm-household production models, because the optimal decisions depend on the covariance of the expected marginal utility with each source of risk, the covariances of the random variables of different sources of risk sources, the expected marginal utility, and risk characteristics of farm inputs.

From equation (3.21), for example, land is allocated to CRP up to the point where the marginal utility of the CRP payment plus the marginal utility of CRP land's contribution to the environment, is equal to the risk adjusted utility of the value of the marginal production forgone. The optimal CRP acreage is not necessary less than in the risk neutral case, and this result depends not only on the risk characteristics of land in production and the covariance between marginal utility and the two elements of risk, but also the covariance term between the two components of risk ($Cov(\eta\varepsilon)$). Using the results from Appendix 3A, if land is a risk increasing input, land in CRP is still possibly less than in the risk neutral case, if the covariance between the two risk factors is high. In this case, the risk-adjusted benefit per unit land in CRP is less than its risk-adjusted cost, and the land in CRP falls until the two terms are equal.

From equation (3.23), labor is employed in agricultural production to the point where the marginal utility of the risk adjusted marginal product of labor is equal to the marginal utility of leisure. From equation (3.22), the marginal utility of leisure relative to consumption is equal to the off-farm wage.

Comparative Static Analysis

Clearly, the best way to determine the effects on optimal input use changes in risk preferences, farm price variability, CRP payments, government policy, etc. is to derive some comparative static results.

To derive tractable results, we make additional assumptions about the utility function. One approach common in the literature on risk is to assume an explicit form for the utility function, and also for the distribution of the random variable associated with either price or yield (Love and Buccola, 1991; Saha, 1994; Chavas and Holt, 1996). Perhaps the most common assumptions are that the random variable is normally distributed and there is a negative exponential utility that embodies the assumption of constant absolute risk aversion (CARA).[17] As an alternative, we assume that the utility function can be approximated by a second-order Taylor series expansion about the mean (Kumbhakar, 2002 and Isik, 2002). Accordingly, we make no specific assumptions about the utility function, or about the distribution of the random variable.

We begin by isolating the effects of price risk and output risk and then examining the set of first-order conditions systematically. If the price is the source of

[17] For example, under the CARA utility preference, the change of the wealth level of the farm household is independent of the farm household production decision; this assumption might not be reasonable in reality.

risk, the first-order conditions from above can be simplified as (see Appendix 3B):

$$(3.24)\quad \frac{1}{U_{\bar{x}}}\frac{\partial Eu(.)}{\partial A_e} = p_e - \overline{p}f_A + \phi\sigma_\eta^2 ff_A + \frac{U_e e_{Ae}}{U_{\bar{x}}} = 0$$

$$(3.25)\quad \frac{1}{U_{\bar{x}}}\frac{\partial Eu(.)}{\partial L_m} = w - \frac{U_l}{U_{\bar{x}}} = 0$$

$$(3.26)\quad \frac{1}{U_{\bar{x}}}\frac{\partial Eu(.)}{\partial L} = \overline{p}f_L - \phi\sigma_\eta^2 ff_L - \frac{U_l}{U_{\bar{x}}} = 0.$$

The economic intuition behind equation (3.24) is straightforward. The optimal CRP acreage is determined when the CRP payment plus the marginal utility of the environmental benefit of CRP equals the mean opportunity cost of land in agricultural production, adjusted for the risk premium. From equation (3.26) labor is allocated to agricultural production up to the point where the marginal utility of leisure is equal to the mean marginal value product of land in agricultural production, adjusted for the risk premium.

Effects of Risk Preferences and the Market Price Variability

The two equations below are the comparative static results reflecting changes in CRP acreage for changes in risk preferences, as represented by Arrow's absolute risk aversion coefficient (ϕ), and exogenous price variability (σ_η^2). They are derived by taking the total derivative of equations (3.24-3.26), and applying Cramer's rule to obtain:[18]

$$(3.27)\quad \frac{\partial A_e}{\partial \phi} = \frac{f\sigma_\eta^2}{\underbrace{U_{\bar{x}}}_{(+)}}\left\{U_{\bar{x}}\underbrace{(\overline{p} - f\phi\sigma_\eta^2)}_{(+)}\underbrace{(f_L f_{LA} - f_A f_{LL})}_{(+)}\underbrace{(\phi w U_l - U_{ll})}_{(+)} + \underbrace{U_e e_{A_e} U_{ll}\phi f_L(\overline{p}f_L - w)}_{(-)}\right\}$$

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[18] All of the comparative static results are based on the assumption that the contribution of environmental externality to the farm household utility is approximated as the first-order derivative. As such, the second- order term is ignored in order for the results to be tractable. The comparative static results in this paper are derived using the Maple software.

$$(3.28)\ \frac{\partial A_e}{\partial \sigma_\eta^2} = \underbrace{\frac{f\phi}{U_{\bar{x}}}}_{(+)} \left\{ U_{\bar{x}} \underbrace{(\bar{p} - f\phi\sigma_\eta^2)}_{(+)} \underbrace{(f_L f_{LA} - f_A f_{LL})}_{(+)} \underbrace{(\phi w U_l - U_{ll})}_{(+)} + \underbrace{U_e e_{A_e} U_{ll} \phi f_L (\bar{p} f_L - w)}_{(-)} \right\}.$$

Proposition 1: *Under price risk, a risk averse farm household will not necessary enroll more acres into CRP if the degree of risk aversion or the variability of market prices increase. However, if the marginal value of CRP's contribution to the environment to the farm household's utility is small, the CRP acreage will increase.*

Discussion: From equation (3.27), there are two effects determining the optimal CRP acre enrollment. The first term in the {.} is the marginal contribution of the consumption multiplied by the effect of leisure. There are three components to the consumption effect. For a well-behaved concave production function (f(.)), we know that the term $(f_L f_{LA} - f_A f_{LL}) > 0$. This guarantees that the sufficiency conditions for the first-and second-order Hessian matrix of the maximum utility problem are satisfied. Further, the terms, $(\phi w U_l - U_{ll})$ and $(\bar{p} - f\phi\sigma_\eta^2)$ should both be positive as well.[19] As such, we know the consumption effect of {.} should contribute positively to CRP acreage.

If the environmental benefits of CRP are valued by the farm household, the marginal utility to CRP acreage is positive. This, combined with the assumptions of

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[19] $$\left|H_{AeAe}\right| = \bar{p} f_{AA} - \phi\sigma_\eta^2 (f_A{}^2 + f f_{AA}) + \frac{(p_e - \bar{p} f_A)\phi\sigma_\eta^2 \lambda f f_A}{\bar{x}} + \frac{U_e e_{Ae} \phi (p_e - \bar{p} f_A)}{U_{\bar{x}}} < 0.$$

$$\left|H_{L_m L_m}\right| = \frac{U_{ll} - U_l w\phi}{U_{\bar{x}}} < 0.$$

$$\left|H_{LL}\right| = \bar{p} f_{LL} - \phi\sigma_\eta^2 (f_L{}^2 + f f_{LL}) + \frac{\bar{p}\phi\sigma_\eta^2 \lambda f f_L{}^2}{\bar{x}} + \frac{U_{ll} - \phi\bar{p} f_L U_l}{U_{\bar{x}}} < 0$$

Sufficiency conditions for all of the Hessian matrixes to be satisfied are: $f_A{}^2 + f f_{AA} > 0$, $p_e - \bar{p} f_A < 0$, $U_{ll} - U_l w\phi < 0$, $f_L{}^2 + f f_{LL} > 0$, $\bar{p} - f\phi\sigma_\eta^2 > 0$. These conditions together are also sufficient for the positive second-order Hessian matrix.

the decreasing marginal utility of leisure and the marginal value of labor in agricultural production is greater than the off-farm wage rate, the second term of {.} will be negative and will partially or totally offset the positive consumption effect on CRP acreage. In sum, the effects of changes in risk preferences and market price variability on CRP acreage are ambiguous; the effects depend on the relative sizes of these two components. However, as the level of risk aversion increases, farm households are more likely increase land in CRP and use less labor in farming if marginal utility of leisure is constant or declining slowly, if farmers place little or no value on the environmental contributions of land of CRP, or if the marginal value product of labor in agriculture is equal to the off-farm wage.

To discuss the effect of the risk preferences and market price variability on the hours worked off the farm, we derive the following comparative static results:

(3.29)

$$\frac{\partial L_m}{\partial \phi} = \frac{f\sigma_\eta^2}{\underbrace{U_{\bar{x}}}_{(+)}} \left\{ \begin{array}{l} U_{\bar{x}} \left\{ \begin{array}{l} U_l \phi[\underbrace{(\bar{p} f_A - p_e)}_{(+)}[\bar{p}\underbrace{(2 f_A f_L f_{LA} - f_A{}^2 f_{LL} - f_L{}^2 f_{AA})}_{(+)} + p_e \underbrace{(f_A f_{LL} - f_L f_{LA})}_{(-)}]] \\ + U_{ll} \underbrace{(\bar{p} - f\phi\sigma_\eta^2)}_{(+)} \underbrace{(f_L f_{AA} - f_A f_{LA})}_{(-)} \end{array} \right\} \\ \underbrace{+ U_{ll} U_e e_{Ae} f\phi \underbrace{(p_e - \bar{p} f_A{}^2)}_{(-)}}_{(+)} \end{array} \right\}$$

(3.30)

$$\frac{\partial L_m}{\partial \sigma_\eta^2} = \frac{f\phi}{\underbrace{U_{\bar{x}}}_{(+)}} \left\{ \begin{array}{l} U_{\bar{x}} \left\{ \begin{array}{l} U_l \phi[\underbrace{(\bar{p} f_A - p_e)}_{(+)}[\underbrace{\bar{p}(2 f_A f_L f_{LA} - f_A{}^2 f_{LL} - f_L{}^2 f_{AA})}_{(+)} + p_e \underbrace{(f_A f_{LL} - f_L f_{LA})}_{(-)}]] \\ + U_{ll} \underbrace{(\bar{p} - f\phi\sigma_\eta^2)}_{(+)} \underbrace{(f_L f_{AA} - f_A f_{LA})}_{(-)} \end{array} \right\} \\ \underbrace{+ U_{ll} U_e e_{Ae} f\phi \underbrace{(p_e - \bar{p} f_A{}^2)}_{(-)}}_{(+)} \end{array} \right\}.$$

Proposition 2: *Under price risk, hours worked off the farm will not necessary increase if the farm household is more risk averse or if there is an increase in market price variability. However, unless CRP payment is very high, more risk averse farm households will work more hours off the farm.*

Discussion: As discussed above, two different effects determine the signs of equations (3.29) and (3.30). The first effect comes from the interaction between post-risk consumption and post-risk leisure. The second effect can be seen as the interaction effect between environmental externality and leisure. Given a quasi-concave production function and sufficiency conditions from the first-and second-order Hessian matrix,[20] we can determine the sign of each term in {.}. Unless the term containing the CRP payment (P_e) is high enough to dominate other terms, this first effect acts to increase the hours worked off the farm. The sign of the second effect should be positive for decreasing marginal utility of leisure.

Similar comparative static results can determine the effect of changes in risk preferences and market price variability on farm labor:

$$(3.31)\ \frac{\partial L}{\partial \phi} = \underbrace{\frac{-f\sigma_\eta^2}{U_{\bar{x}}}}_{(-)} \left\{ \underbrace{U_{\bar{x}} \underbrace{(\bar{p} - f\phi\sigma_\eta^2)}_{(+)} \underbrace{(f_L f_{AA} - f_A f_{LA})}_{(-)} \underbrace{(U_{ll} - w\phi U_l)}_{(-)}}_{(+)} + \underbrace{U_{ll} U_e e_{Ae} f_L \phi \underbrace{(p_e - \bar{p} f_A)}_{(-)}}_{(+)} \right\}$$

$$(3.32)\ \frac{\partial L}{\partial \sigma_\eta^2} = \underbrace{\frac{-f\phi}{U_{\bar{x}}}}_{(-)} \left\{ \underbrace{U_{\bar{x}} \underbrace{(\bar{p} - f\phi\sigma_\eta^2)}_{(+)} \underbrace{(f_L f_{AA} - f_A f_{LA})}_{(-)} \underbrace{(U_{ll} - w\phi U_l)}_{(-)}}_{(+)} + \underbrace{U_{ll} U_e e_{Ae} f_L \phi \underbrace{(p_e - \bar{p} f_A)}_{(-)}}_{(+)} \right\}.$$

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[20] The important conditions are: $(pf_A - p_e > 0)$, $(2 f_A f_L f_{LA} - f_A^2 f_{LL} - f_L^2 f_{AA}) > 0$, $(f_A f_{LL} - f_L f_{LA}) < 0$, $(\bar{p} - f\phi\sigma_\eta^2) > 0$, and $(f_L f_{AA} - f_A f_{LA}) < 0$.

Proposition 3: *Under price risk, hours worked on the farm will unambiguously decrease for more risk averse farm households, or if there is an increase in market price variability.*

Discussion: As we discussed above, two terms in {.} in equations (3.31-3.32) determine the effects on farm labor. The first term in {.} is the interaction between marginal consumption and leisure, while the second term is the interaction between the marginal utility of CRP value to the environmental quality and the first-and second-order effects of the utility of leisure. Combining the assumptions of decreasing marginal utility of leisure with the quasi- concavity of production, we can conclude that both the first-and second-effects in equations (3.31-3.32) contribute negatively labor in farm production.

Effects of Decoupled Payments

In recent years, decoupled payments, the pure income transfer to the farm households, are thought by many to have no effect on farm production decisions, particularly in a certain world. However, it is not necessarily true when risk is considered explicitly. If the payments are "fully decoupled", the only effect recognized is the "wealth effect", since decoupled payments will improve the farm income. As such, if the risk attitude is independent of farm household wealth, a fully decoupled payment has no effect on the optimal farm production decisions (Hennessy, 1998; Antou and Mouel, 2004). Since we allow for a "wealth effect" and do not limit our attention to the case of CARA, we provide general comparative static results to determine the effects of changes in decoupled payments on CRP acreage, off-farm work, and labor used on the farm:

(3.33)

$$\frac{\partial A_e}{\partial M}=\underbrace{\frac{\phi U_{ll}}{\bar{x}U_{\bar{x}}^{\ 2}}}_{(-)}\left\{\underbrace{\lambda f\sigma_\eta^2 U_{\bar{x}}\underbrace{(\bar{p}-f\phi\sigma_\eta^2)}_{(+)}\underbrace{(f_L f_{LA}-f_A f_{LL})}_{(+)}}_{(+)}+U_e e_{A_e}\bar{x}\underbrace{[\underbrace{f_{LL}(\bar{p}-\phi\sigma_\eta^2 f)}_{(-)}-\underbrace{\phi\sigma_\eta^2 f_L^{\ 2}}_{(-)}]}_{(-)}\right\}$$

(3.34)

$$\frac{\partial L_m}{\partial M}=\underbrace{\frac{-\phi}{xU_{\bar{x}}^{\ 2}}}_{(-)}\left\{\begin{array}{l} U_{\bar{x}}U_l\bar{x}\left\{\begin{array}{l}\underbrace{(\phi\sigma_\eta^2 f-\bar{p})}_{(-)}[\underbrace{f_A^{\ 2}f_{LL}+f_L^{\ 2}f_{LA}-2f_A f_L f_{LA}+\phi\sigma_\eta^2 f(f_{AA}f_{LL}-f_{LA}^{\ 2})}_{(-)}]\\ +\bar{p}^2\underbrace{(f_{AA}f_{LL}-f_{LA}^{\ 2})}_{(+)}\end{array}\right\}\\ \underbrace{U_x U_{ll}\lambda\sigma_\eta^2 f\underbrace{(\bar{p}-\phi\sigma_\eta^2 f)(f_L f_{AA}-f_A f_{LA})}_{(-)}}_{(+)}+U_{ll}U_e e_{Ae}\bar{x}[\underbrace{f_{LA}(\bar{p}-\phi\sigma_\eta^2 f)-\phi\sigma_\eta^2 f_A f_L}_{(?)}]\end{array}\right\}$$

(3.35)

$$\frac{\partial L}{\partial M}=\underbrace{\frac{-U_{ll}\phi}{\bar{x}U_{\bar{x}}^{\ 2}}}_{(+)}\left\{U_{\bar{x}}\lambda f\sigma_\eta^2\underbrace{(\bar{p}-f\phi\sigma_\eta^2)(f_A f_{LA}-f_L f_{AA})}_{(+)}+U_e e_{Ae}\bar{x}[\underbrace{f_{LA}(f\phi\sigma_\eta^2-\bar{p})+f_A f_L\phi\sigma_\eta^2}_{(?)}]\right\}.$$

The parameter (λ) is the elasticity of absolute risk aversion at the expected post-risk consumption (Just and Zilberman 1983), and it is defined as: $\lambda=-\frac{\partial\phi(\bar{x})}{\partial\bar{x}}\frac{\bar{x}}{\phi(\bar{x})}$.

When λ is positive (zero), absolute risk aversion is decreasing (constant).

Proposition 4: *Under price risk, the change in CRP acreage, hours worked off the farm, and hours worked on the farm are ambiguous relative to a change in decoupled payments. These effects depend on the marginal utility of post-risk consumption, leisure, and the environmental externality. Specifically, if the environmental value of CRP externality is ignored or is small, CRP acreage and off-farm work decrease, and* *farm work increases with higher decoupled payments. If risk preferences are CARA, increasing decoupled payments results in more CRP acreage.*

Discussion: In this case, there are three terms in equation (3.33) that determine changes in CRP acreage. The first is the fact that the term outside the {.} is negative. Thus, if we can sign the terms in the {.}, the final effect will be in the opposite direction. The first term in {.} is the consumption effect, which is positive, but given that the marginal utility of leisure is declining, this term's overall contribution to determining the change in CRP acreage is negative. The second term of {.} is related to the marginal utility of CRP's contribution to the environment. This term is negative, but when multiplied by the term outside the {.}, the overall effect is positive. The net effect of a change in decoupled payments depends on the relative sizes of the two effects. Thus, as decoupled payments increase, fewer acres are in CRP if the marginal utility of CRP contribution to the environment is ignored or assumed to be very small.

Perhaps the most interesting conclusion is the fact that decoupled payments affect land in CRP acres, even if risk preferences are CARA, the case where $\lambda = 0$. In this case, the decoupled payment effect on land in CRP still comes from the marginal utility of CRP's contribution to the environment. This is in contrast to some existing literature, but in a certain world ($\phi = 0$), we also find that decoupled payments have no effect on input allocation of the farm household.

The effect of decoupled payments on off-farm hours is difficult to disentangle. There are three terms in {.} that must be considered. The first term of {.} reflects the interaction between the marginal utilities of consumption and leisure, while the second term of {.} is the interaction between the marginal utility of consumption and the rate of change in the marginal utility of leisure. Again, we can determine that these two terms are both positive in {.}, but because the term outside the {.} is negative, a change in decoupled payments reduces the work off the farm. The combined effects of these two terms can be regarded as the “income effect” of decoupled payments, and it is negative, as one would expect. However, it is the size and the sign of the third term in {.} that will ultimately determine the overall effect of decoupled payments on off-farm work. This third term of {.} is the interaction between the marginal utility of leisure and the marginal utility of the environmental effects of CRP. Since we cannot sign ($f_{LA}(\overline{p}-\phi\sigma_{\eta}^{2}f)-\phi\sigma_{\eta}^{2}f_{A}f$), we cannot sign of this third term either. However, if this term is negative, it reinforces the income effect, and the overall effect of decoupled payments on off-farm working hours is negative. This would also be true if the farmer’s marginal utility for the environmental effects of CRP are low, or rate of change in the marginal utility of leisure is small.

We encounter similar difficulties in interpreting the effects of changes in decoupled payments on farm work in equation (3.35). The income effect, the first term in {.}, acts to increase the amount of farm labor as decoupled payments rise, while, as in the case of equation (3.34), the remaining term contains the marginal utility of the environment, and it cannot be signed.

Own and Cross Price Effects

From the first-order conditions of the optimal input allocation of the farm household (equations 3.24-3.26), we know that the off-farm wage should affect the decision of to enroll land in CRP; CRP payments should also help determine the amount worked off the farm. The relative sizes of these own-and cross-price effects are examined in the following comparative static results:[21]

$$(3.36)\ \frac{\partial A_e}{\partial p_e}=\underbrace{\frac{w\phi U_l}{U_{\bar{x}}}}_{(+)}\underbrace{[\phi\sigma_{\eta}^{2}(\underbrace{ff_{LL}+f_L{}^2}_{(+)})-\overline{p}f_{LL}]}_{(+)}$$

[21] Due to its complexity otherwise, we impose the condition, U_{ll}=0, to derive the results in equations (3.36-3.39).

(3.37)

$$\frac{\partial L_m}{\partial w} = \underbrace{\frac{\phi L_m U_l}{\bar{x} U_{\bar{x}}}}_{(+)} \left\{ \underbrace{(\phi \sigma_\eta^2 f - \bar{p})}_{(-)} [\underbrace{\phi \sigma_\eta^2 (f_L{}^2 f_{AA} + f_A{}^2 f_{LL} - 2 f_A f_L f_{LA})}_{(-)} + \underbrace{(\bar{p} - \phi \sigma_\eta^2 f)}_{(+)} \underbrace{(f_{LA}{}^2 - f_{LL} f_{AA})}_{(+)} \right\}$$

$$(3.38)\ \frac{\partial L_m}{\partial p_e} = \underbrace{\frac{-\phi U_l}{U_{\bar{x}}}}_{(-)} \left\{ \begin{array}{l} A_e \left\{ \begin{array}{l} \bar{p}^2 \underbrace{(f_{AA} f_{LL} - f_{LA}{}^2)}_{(+)} + \phi \sigma_\eta^2 \underbrace{(\bar{p} - f \phi \sigma_\eta^2)}_{(+)} \\ [\underbrace{2 f_A f_L f_{LA} - f_L{}^2 f_{AA} - f_A{}^2 f_{LL}}_{(+)} + f \underbrace{(f_{LA}{}^2 - f_{AA} f_{LL})}_{(-)}] \end{array} \right\} \\ + \underbrace{(\bar{p} - f \phi \sigma_\eta^2)}_{(+)} [\underbrace{f_{LL} (\bar{p} f_a - p_e) - p f_A f_{LA}}_{(-)}] + \underbrace{p_e \phi \sigma_\eta^2 f_L{}^2}_{(+)} \end{array} \right\}$$

(3.39)

$$\frac{\partial A_e}{\partial w} = \underbrace{\frac{-\phi L_m U_{ll}}{\bar{x} U_{\bar{x}}}}_{(+)} \left\{ U_{\bar{x}} \lambda f \sigma_\eta^2 \underbrace{(\bar{p} - \phi \sigma_\eta^2 f)(f_L f_{LA} - f_A f_{LL})}_{(+)} + U_e e_{Ae} \bar{x} [\underbrace{f_{LL} (\bar{p} - \phi \sigma_\eta^2 f) - \phi \sigma_\eta^2 f_L{}^2}_{(-)}] \right\}$$

.

Proposition 5: *Under price risk and by ignoring the second-order derivative of utility with respect to leisure, CRP acreage and off-farm work increase in response to own price changes. However, the cross price effects are ambiguous in general. Specifically, if the effect of the environmental externality is small, increasing the off-farm wage results in more acreage enrolled in CRP.*

Discussion: Equations (3.36-3.37) are the comparative static results of the own price response of CRP acres and off farm worked hours. Given the sufficient conditions to insure the first and second order Hessian are satisfied and the concavity of the production function, the own price response is unambiguously positive. The own price increases provide the direct incentives for CRP acre enrollment and off-farm worked hours.

Equations (3.38-3.39) are the comparative static results of the cross price effects. As before, the sufficient conditions and the nature of the production function help to determine each term of these two equations. The cross price effect of per acre CRP payment to off-farm work is complicated; thus, the effect is undetermined. The total effect depends on the nature of production, risk preferences, and the mean market price and the per acre CRP payment. Compared to equation (3.38), the cross price effect of CRP acreage response to a change in the off-farm wage is clear. Two effects determine the total effect of equation (3.39). The first term in {.} is the income effect based on the post-risk consumption, which contributes positively to CRP enrollment. The second term is the effect of the environmental externality as the off-farm wage increases. The effect contributes negatively to CRP acreage. Thus, if the marginal contribution of the environmental externality to utility is small or is ignored, it is likely that the farm household will increase the CRP acreage with an increase in the off-farm wage. As this off-farm wage increases, the farmer will, under these conditions find an added incentive to enroll more land in CRP at the going CRP payment.

APPENDIX 3A: Covariance Analysis

$$x = (\overline{P} + \eta)(f + g\varepsilon - hu) + wL_m + P_e A_e = E(x) + \overline{P}(g\varepsilon - hu) + \eta(f + g\varepsilon - hu)$$

Assume $g\varepsilon - hu > 0$ and $f + g\varepsilon - hu >$ 0, If $\eta > 0$, then $x > E(x)$. Under the assumption of risk aversion, *U'(x) < U'(E(x))*. Therefore, we have Cov (U_x', η) < 0.

The same argument can be applied to determine the signs on the other terms.

Therefore, we know that *Cov* (U_x', ε) < 0 and *Cov* (U_x', *u*) > 0.

APPENDIX 3B: Deriving the First-Order Condition Systems

Using the household consumption constraint (equation (3.2) in the text), the expression for the difference in consumption around the expected post-risk consumption level follows immediately as:

(3B1) $\bar{x} = \bar{p}(f - h\bar{u}) + p_e A_e + M$

(3B2) $x - \bar{x} = \bar{p}g\varepsilon + \eta(f + g\varepsilon - hu)$

If the utility function can be properly approximated around the expected post-risk consumption level using a Taylor's series expansions with only the first two moments, the approximation for marginal utility ($U_{\bar{x}}$) is:

(3B3) $U_x = U_{\bar{x}} + U_{\bar{x}\bar{x}}(x - \bar{x}) = U_{\bar{x}} + U_{\bar{x}\bar{x}}[\bar{p}g\varepsilon + \eta(f + g\varepsilon - hu)]$

Replacing the expressions for marginal utility in equations (3.6) and (3.7) from the text with equation (3B3), the first-order conditions can be expressed as:

(3B4)

$$\frac{\partial Eu(.)}{\partial A_e} = E\{\{-U_{\bar{x}} - U_{\bar{x}\bar{x}}[\bar{p}g\varepsilon + \eta(f + g\varepsilon - hu)]\}[(\bar{p} + \eta)(f_L + g_L\varepsilon - h_L u) + p_e] + U_e e_{Ae}\}$$

(3B5) $$\frac{\partial Eu(.)}{\partial L_m} = E\{U_{\bar{x}} + U_{\bar{x}\bar{x}}[\bar{p}g\varepsilon + \eta(f + g\varepsilon - hu)] - U_l\}$$

(3B6)

$$\frac{\partial Eu(.)}{\partial L} = E\{\{U_{\bar{x}} + U_{\bar{x}\bar{x}}[\bar{p}g\varepsilon + \eta(f + g\varepsilon - hu)]\}[(\bar{p} + \eta)(f_L + g_L\varepsilon - h_L u) + p_e] - U_l\}$$

If both right-and left-hand sides of equations (3B4) and (3B5) are divided by ($U_{\bar{x}}$), and we substitute Arrow's measure of absolute risk aversion, ($\phi(\bar{x}) = \frac{-U_{\bar{x}\bar{x}}}{U_{\bar{x}}}$), and eliminate the expectation operators, equations (3B4) and (3B5) become:

(3B7) $$\frac{1}{U_{\bar{x}}}\frac{\partial Eu(.)}{\partial A_e} = -\overline{p}(f_A - h_A\overline{u}) + \phi[gg_A\sigma_\varepsilon^2(\overline{p}^2 + \sigma_\eta^2) + \sigma_\eta^2(ff_A + hh_A\sigma_u^2)] + \frac{U_e e_{Ae}}{U_{\bar{x}}}$$

(3B8) $$\frac{1}{U_{\bar{x}}}\frac{\partial Eu(.)}{\partial L_m} = w - \frac{U_l}{U_{\bar{x}}}$$

(3B9) $$\frac{1}{U_{\bar{x}}}\frac{\partial Eu(.)}{\partial L} = p_e + \overline{p}(f_L - h_L\overline{u}) - \phi[gg_L\sigma_\varepsilon^2(\overline{p}^2 + \sigma_\eta^2) + \sigma_\eta^2(ff_L + hh_L\sigma_u^2)] - \frac{U_l}{U_{\bar{x}}}$$

When only price risk is considered, the first-order equation system can be simplified as equations (3.24-3.26) in the text. For this case, by taking the total derivative of the first-order equation system (3B7-3B9), and applying the Cramer's rule, we can obtain the comparative static results in the text (equations 3.24-3.39).

CHAPTER FOUR

SEQUENTIAL CRP PARTICIPATION DECISIONS AND FARM PRODUCTIVITY

Introduction

By retiring the sensitive cropland from crop production, the Conservation Reserve Program (CRP) has substantially reduced soil erosion and improved the environmental quality with a fairly high cost paid to the farms to buy the land out of production. The focus of this chapter is threefold. First, there is an analysis of farm household toward CRP participation behavior. Second, equations for per acre CRP payment and acreage enrollment response are estimated. Finally, the effects of CRP participation on technical efficiency, scale efficiency, and productivity of farm production are estimated.

One special feature of CRP is that the CRP participants may be categorized into two groups, depending on their degree of participation: *whole CRP farm* and *partial CRP farm*. The whole CRP farm enrollees are defined as for those farms, where most or all the cropland is enrolled in CRP and there are no farm commodities. The partial CRP enrollees are those who participate in CRP and maintain a proportion of their land in farming.[22] By recognizing the differences between the whole and partial CRP participants, rather than simply regarding the CRP participation decision as a binary decision, it is possible to isolate the separate effects of factors affecting the types of participation. Such a distinction is also essential in determining the effects of participation decisions on farm productivity, because whole farm CRP participants produce no farm sales. To investigate the effects of CRP participation decisions on farm productivity, it only makes sense to compare the partial farm CRP participants to

[22] We follow the definition of Sullivan, *et al.* (2004) to define whole and partial farm CRP enrollees. In their report, they also state that "it is useful to synthesize the diversity of program participants into two groups-whole farm enrollees and partial farm enrollees."

the non-participant groups.

In contrast to previous studies that focus solely on the binary participation case,[23] the distinction between whole farm and partial farm CRP participants leads to a sequential two-decision model related to CRP participation. In the first, the farm household decides on whether or not to participate in CRP. This can be regarded as a binary discrete choice decision as in other conventional studies. Next, given that the farm household decides to participate in CRP, the second decision by the farm household sequentially is whether to enroll the entire farm or only part of it into CRP. In drawing this distinction, we can determine if different factors affect two stages of this CRP participation decision process. Modeling the CRP participation decision in a sequential discrete choice framework also helps to distinguish separate factors affecting the degree of participation. To the best of our knowledge, no one attempted to model the CRP participation decision in this way.

Econometric Framework

When sequential choices are considered, we can view the alternatives by using a decision tree, grouping the full set of the potential choices into several subgroups. The model structure is in Figure 4.1. This figure also determines the second stage equations estimated for each subgroup at each stage.

[23] For example, McLean, Hui, and Joseph (1994) analyze the environmental program participation decision of Louisiana farmers using the binary logit model.

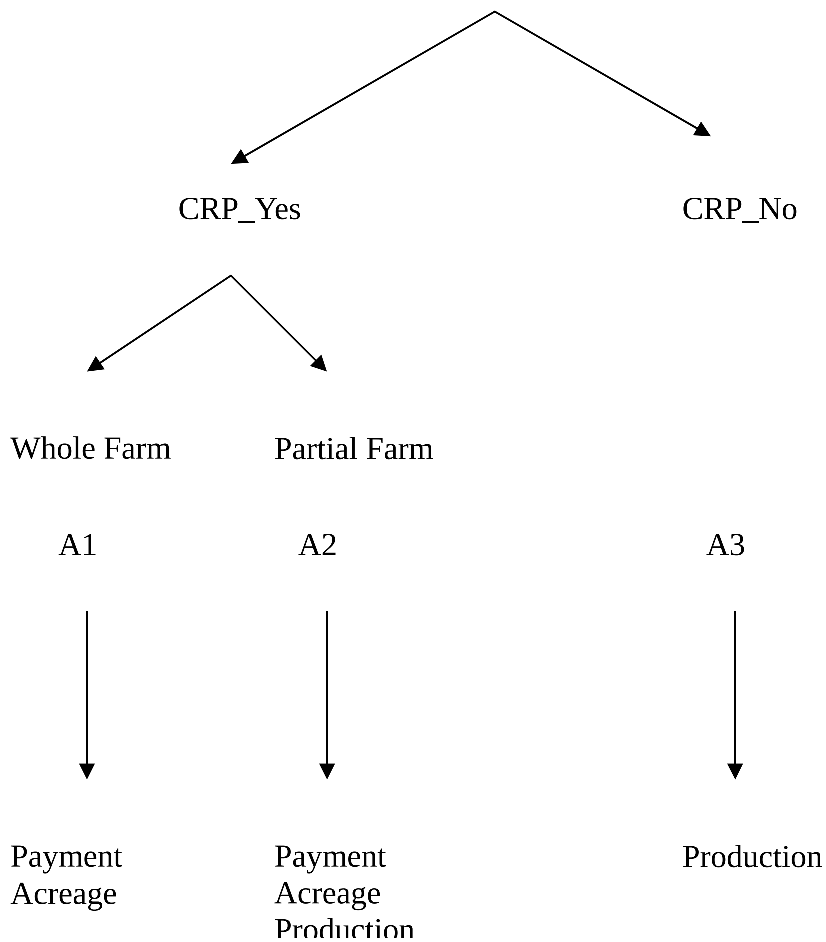

Figure 4.1: Model Structure of the CRP Sequential Choice

According to Figure 4.1, three different regimes can be realized from the observed data. For the whole CRP farms (regime A1), we only observe CRP payments and CRP acreage, by definition. For the partial CRP farms (regime A2), one also has data on CRP payments and acreage enrolled, and farm production. These farms enroll only a fraction of their land in CRP and continue to farm the remaining land. For the CRP non-participants (regime A3), we observe only farm production. To sum, we estimate these particular equations: CRP payment, CRP enrollment, and farm production.

To conduct the analysis, we employ a three-stage econometric estimation based on Heckman's self-selection approach (1976; 1979). In the first stage, we focus on the sequential CRP participation decisions. Given the estimates of the participation equation, the CRP payment and acre equations are estimated based on the observations for each regime. In the third stage, we analyze the effects of CRP participation on technical and scale efficiencies and farm productivity.

Sequential CRP Choice Model

The pioneering work on sequential decisions is the model proposed by Amemiya (1985), which he refers to as the sequential probit model. Amemiya's model regards the sequential decision process simply as two uncorrelated binary probit choices. However, this particular assumption is not necessary, although it provides for simple interpretation and implementation. In subsequent analysis, Abowd and Farber (1982), Poirier (1980), Tunali (1986) relax this uncorrelation assumption, and propose the sequential choice model allowing for some degree of correlation between the sequential choices. Amemiya's model is simply a special sequential case of this more general model. Tunali's (1986) formulation is most appropriate for our purpose. [24] In that model, each choice stage can be specified as the binary probit model, but there is correlation between them:

(4.1) $D_1{*} = z_1{'}r_1 + \varepsilon_1$ $\quad D_1=1$ iff $D_1{*}>0$

$D_2{*} = z_2{'}r_2 + \varepsilon_2$ $\quad D_2=1$ iff $D_2{*}>0$

[24] Tunali (1986) studies the sequential choice of migration/re-migration process. That is: if people choose to stay, then there is no re-migration decision observable. The same model has been applied to the labor market literature by Henneberger and Sousa_Poza (1998). People report their wage only when they choose to work. Khanna (2001) applied this model to the field of agricultural economics. She studied the nitrogen productivity under the sequential choice of two site-specific technologies adoption.

We assume the error terms ($\varepsilon_1, \varepsilon_2$) following the bivariate normal distribution: $N\left\{(0,0);\begin{bmatrix} 1 & \rho_{12} \\ \rho_{12} & 1 \end{bmatrix}\right\}$, where z are the parameters of interest in each choice equation, r is the individual covariance. D_1* is the latent variable for CRP participation decision, D_2* is the latent variable for the partial farm CRP participation decision given the CRP participation.[25]

The observability condition of this model can be shown as:

D_1=1 iff the farm household participates in CRP; it is zero otherwise;

D_2=1 if the farm household participates in CRP as a partial CRP farm participant; given the initial decision to participate in CRP. D_2 is observed only when D_1=1.

Based on this observability rule, our model is one with an incomplete classification of the observed outcomes. The probability of participation in each regime can be shown as (from equation 4.1):

(4.2)

$$\Pr ob(A_1) = \Pr(D_1 = 1, D_2 = 0) = \Pr(\varepsilon_1 > -z_1' r_1, \varepsilon_2 < -z_2' r_2) = \Phi(z_1' r_1, -z_2' r_2, -\rho_{12})$$

$$\Pr ob(A_2) = \Pr(D_1 = 1, D_2 = 1) = \Pr(\varepsilon_1 > -z_1' r_1, \varepsilon_2 > -z_2' r_2) = \Phi(z_1' r_1, z_2' r_2, \rho_{12})$$

$$\Pr ob(A_3) = \Pr(D_1 = 0) = \Pr(\varepsilon_1 < -z_1' r_1) = 1 - \Phi(z_1' r_1)$$

Given these probabilities of the each outcome, this sequential choice model can be estimated by the maximum likelihood estimation; the likelihood function is:

$$(4.3) \quad L = \prod_{A_2} \Phi(z_1' r_1, z_2' r_2, \rho_{12}) . \prod_{A_1} \Phi(z_1' r_1, -z_2' r_2, -\rho_{12}) . \prod_{A_3} \{1 - \Phi(z_1' r_1)\}$$

[25] Since the second stage decisions (whole *vs* partial CRP farm) are mutually exclusive, only one participation equation is needed at this stage. Without loss of generality, we assume the partial CRP decision as the second choice decision.

Second Stage Equation System

The second stage outcomes of interest are the CRP per-acre payment, and CRP acreage enrollment equations. Since the CRP payment and acreage are observed only for those who decide to participate in CRP, there are no equations to be estimated for regime A3 in Figure 4.1. Suppose the CRP payment and CRP acreage equations are specified as:

(4.4) $P = \alpha_p ' X_p + e_p$

(4.5) $A = \beta_p P + \alpha_a ' X_a + e_a$

where P is the CRP price and A is CRP acreage; $(\alpha_p, \alpha_a, \beta_p)$ are the parameters of interest, and (X_p, X_a) are the individual characteristics. To obtain a tractable result, the error terms of equations (4.4-4.5) are assumed to be uncorrelated. However, each of them is correlated with equation (4.1) as a trivariate normal distribution. To investigate the CRP price effects on CRP acreage, the price variable (P) is specified as one of the right hand side variables of equation (4.5).

To obtain the consistent estimates of equation (4.4-4.5), two empirical issues must be addressed: self-selection and the endogeneity. The first problem can be overcome by following Heckman's approach by adding the appropriate Inverse Mills Ratios as new right hand side variables in equation (4.4-4.5) to correct for the self-selection problem. However, the correction differs by regime. After correcting for the self-selection bias, linear regression (OLS) provides consistent estimates of equation (4.4-4.5) of each regime. However, applying linear estimation of equation (4.5) after accounting for self-selection might still lead to inconsistent estimation if CRP price is endogenous to the CRP acreage. To account for the endogeneity between CRP price and acreage, we first estimate price equation (4.4) following Heckman's approach and calculate the predicted CRP price for use as an instrumental variable for the observed

CRP price in equation (4.5).[26] We express the appropriate second stage equations of each regime below:

In regime A1, the expected CRP payment and CRP acreage equations are:

(4.6) $E(P \mid D_1 = 1, D_2 = 0) = \alpha_P ' X_P + E(e_P \mid \varepsilon_1 > -z_1 ' r_1, \varepsilon_2 < -z_2 ' r_2)$

$$= \alpha_P ' X_P + \sigma_{P1} \frac{\phi(z_1 ' r_1)}{\Phi(z_1 ' r_1, -z_2 ' r_2, -\rho_{12})} \Phi[\frac{-z_2 ' r_2 + \rho_{12} z_1 ' r_1}{\sqrt{1-\rho_{12}{}^2}}]$$

$$+ \sigma_{P2} \frac{\phi(z_2 ' r_2)}{\Phi(z_1 ' r_1, -z_2 ' r_2, -\rho_{12})} \Phi[\frac{z_1 ' r_1 - \rho_{12} z_2 ' r_2}{\sqrt{1-\rho_{12}{}^2}}]$$

$$= \alpha_P ' X_P + \sigma_{P1} \lambda_1 + \sigma_{P2} \lambda_2$$

(4.7) $E(A \mid D_1 = 1, D_2 = 0) = \beta_p \hat{P} + \alpha_A ' X_A + E(e_A \mid \varepsilon_1 > -z_1 ' r_1, \varepsilon_2 < -z_2 ' r_2)$

$$= \beta_p \hat{P} + \alpha_A ' X_A + \sigma_{A1} \frac{\phi(z_1 ' r_1)}{\Phi(z_1 ' r_1, -z_2 ' r_2, -\rho_{12})} \Phi[\frac{-z_2 ' r_2 + \rho_{12} z_1 ' r_1}{\sqrt{1-\rho_{12}{}^2}}]$$

$$+ \sigma_{A2} \frac{\phi(z_2 ' r_2)}{\Phi(z_1 ' r_1, -z_2 ' r_2, -\rho_{12})} \Phi[\frac{z_1 ' r_1 - \rho_{12} z_2 ' r_2}{\sqrt{1-\rho_{12}{}^2}}]$$

$$= \beta_p \hat{P} + \alpha_A ' X_A + \sigma_{A1} \lambda_1 + \sigma_{A2} \lambda_2$$

For regime A2, the expected CRP payment, and CRP acreage equations can be written as:

(4.8) $E(P \mid D_1 = 1, D_2 = 1) = \alpha_p ' X_p + E(e_p \mid \varepsilon_1 > -z_1 ' r_1, \varepsilon_2 > -z_2 ' r_2)$

$$= \alpha_p ' X_p + \sigma_{p1} \frac{\phi(z_1 ' r_1)}{\Phi(z_1 ' r_1, z_2 ' r_2, \rho_{12})} \Phi[\frac{z_2 ' r_2 - \rho_{12} z_1 ' r_1}{\sqrt{1-\rho_{12}{}^2}}]$$

$$+ \sigma_{p2} \frac{\phi(z_2 ' r_2)}{\Phi(z_1 ' r_1, z_2 ' r_2, \rho_{12})} \Phi[\frac{z_1 ' r_1 - \rho_{12} z_2 ' r_2}{\sqrt{1-\rho_{12}{}^2}}]$$

$$= \alpha_p ' X_p + \sigma_{p1} \lambda_1 + \sigma_{p2} \lambda_2$$

[26] This strategy is commonly used in labor economics (Killingsworth, 1983 and Fernandez, Rodriguez and Sperlich, 2001).

$$(4.9)\quad E(A \mid D_1 = 1, D_2 = 1) = \beta_p \hat{P} + \alpha_A' X_A + E(e_A \mid \varepsilon_1 > -z_1' r_1, \varepsilon_2 > -z_2' r_2)$$

$$= \beta_p \hat{P} + \alpha_A' X_A + \sigma_{A1} \frac{\phi(z_1' r_1)}{\Phi(z_1' r_1, z_2' r_2, \rho_{12})} \Phi[\frac{z_2' r_2 - \rho_{12} z_1' r_1}{\sqrt{1-\rho_{12}^2}}]$$

$$+ \sigma_{A2} \frac{\phi(z_2' r_2)}{\Phi(z_1' r_1, z_2' r_2, \rho_{12})} \Phi[\frac{z_1' r_1 - \rho_{12} z_2' r_2}{\sqrt{1-\rho_{12}^2}}]$$

$$= \beta_p \hat{P} + \alpha_p' X_p + \sigma_{p1} \lambda_1 + \sigma_{p2} \lambda_2$$

One should note that the estimated variance of the second stage is incorrect, based on an argument similar to that for the binary choice sample selection model (Heckman 1979). As such, we have to correct for both endogenous selection for the two choices and heteroscedasticity problems.[27]

Analysis of Farm Productivity and Efficiencies

In order to understand the effects of the sequential CRP participation decisions on farm productivity, we utilize the two-stage method of moments to estimate the production function and the technical efficiency of each farmer in each group. Furthermore, we study the relative technical and scale efficiencies, and relative

[27]Similar to the standard binary choice sample selection model by Heckman (1979) and Greene (1981), the variance-covariance matrix of the second stage estimators should be corrected for both endogenous selection and the heteroscedasticity problems. The correct variance-covariance matrix is (Greene 1998):

$$V = (X^{*\prime} X^*)^{-1}[X^{*\prime}(\sigma^2 I - \prod) X^* + \theta_1^2 X^{*\prime} G_1 \Sigma G_1' X^* + \theta_2^2 X^{*\prime} G_2 \Sigma G_2' X^*](X^{*\prime} X^*)^{-1}$$

where:

$$X^* = [X, \lambda_1, \lambda_2]$$

$$\prod = diag\{\pi_1, \pi_2, ...\pi_N\}$$

$$\pi_i = \theta_1^2(-z_1' x_1)\lambda_1 + \theta_2^2(-z_2' x_2)\lambda_2 + (\theta_1\lambda_1 + \theta_2\lambda_2)^2 - [2\theta_1\theta_2 - \rho(\theta_1^2 + \theta_2^2)] \frac{\phi(-z_1' x_1, -z_2' x_2, \rho)}{\Phi(-z_1' x_1, -z_2' x_2, \rho)}$$

Σ is the asymptotic covariance matrix of the sequential choice model:

$$G_j = \frac{\partial \lambda_j}{\partial[z_1, z_2, \rho_{12}]} \qquad j = 1,2$$

The first term of the terms in [.] is used for correcting the heteroscedasticity (White (1980)), while the second term of [.] is used for correcting the endogenous selection problem for the binary CRP decision, and the third term is used for correcting the partial CRP decision.

technology differences between groups by decomposing the Malqumist index of Total Factor Productivity (TFP). In so doing, we are able to understand the impact of the sequential CRP participation decisions on technical and scale efficiencies, and farm productivity.

Estimating the Production Functions

To begin the analysis related to technical efficiency and productivity, we estimate a production function for each of the two groups (Partial CRP participants and non-participants). This is possible because farm production and input levels are observed for each farmer in these two groups. These two production function can be specified as:

(4.10) $$Y_1 = \beta_1' X_1 + \xi_1 \quad \text{and} \quad Y_0 = \beta_0' X_0 + \xi_0 ,$$

where Y_1 and Y_0 are the production functions for partial CRP participants, and non-participants, respectively. Accordingly, the conditional expected production levels of each group, under the trivariate normality assumption for $(\varepsilon_1, \varepsilon_2, \xi_1)$, $(\varepsilon_1, \varepsilon_2, \xi_0)$, are:

(4.11) $$E(Y_1 \mid I_1 = 1, I_2 = 1) = \beta_1' X_1 + E(\xi_1 \mid I_1 = 1, I_2 = 1)$$

$$= \beta_1' X_1 + \sigma_{p1} \frac{\phi(z_1' r_1)}{\Phi(z_1' r_1, z_2' r_2, \rho_{12})} \Phi[\frac{z_2' r_2 - \rho_{12} z_1' r_1}{\sqrt{1-\rho_{12}^2}}]$$

$$+ \sigma_{p2} \frac{\phi(z_2' r_2)}{\Phi(z_1' r_1, z_2' r_2, \rho_{12})} \Phi[\frac{z_1' r_1 - \rho_{12} z_2' r_2}{\sqrt{1-\rho_{12}^2}}]$$

$$E(Y_0 \mid I = 0) = \beta_0' X_0 + E(\xi_0 \mid I = 0) = \beta_0' X_0 - \sigma_{\rho_0} \frac{\phi(z_1' r_1)}{1 - \Phi(z_1' r_1)}$$

Using this result, equation (4.11) can be rewritten as equation (4.12):[28]

[28] Note that equation (4.12) is the same as the binary choice model for off-farm labor supply only, since the non-CRP participants don't make any decision regarding either whole or partial CRP farm decisions.

$$Y_1 = \beta_1' X_1 + \sigma_{p1} \frac{\phi(z_1' r_1)}{\Phi(z_1' r_1, z_2' r_2, \rho_{12})} \Phi[\frac{z_2' r_2 - \rho_{12} z_1' r_1}{\sqrt{1-\rho_{12}^2}}] + \sigma_{p2} \frac{\phi(z_2' r_2)}{\Phi(z_1' r_1, z_2' r_2, \rho_{12})} \Phi[\frac{z_1' r_1 - \rho_{12} z_2' r_2}{\sqrt{1-\rho_{12}^2}}]$$

$$+ \left\{ \xi_1 - \sigma_{p1} \frac{\phi(z_1' r_1)}{\Phi(z_1' r_1, z_2' r_2, \rho_{12})} \Phi[\frac{z_2' r_2 - \rho_{12} z_1' r_1}{\sqrt{1-\rho_{12}^2}}] - \sigma_{p2} \frac{\phi(z_2' r_2)}{\Phi(z_1' r_1, z_2' r_2, \rho_{12})} \Phi[\frac{z_1' r_1 - \rho_{12} z_2' r_2}{\sqrt{1-\rho_{12}^2}}] \right\}$$

$$= \beta_1' X_1 + \sigma_{p1} \frac{\phi(z_1' r_1)}{\Phi(z_1' r_1, z_2' r_2, \rho_{12})} \Phi[\frac{z_2' r_2 - \rho_{12} z_1' r_1}{\sqrt{1-\rho_{12}^2}}] + \sigma_{p2} \frac{\phi(z_2' r_2)}{\Phi(z_1' r_1, z_2' r_2, \rho_{12})} \Phi[\frac{z_1' r_1 - \rho_{12} z_2' r_2}{\sqrt{1-\rho_{12}^2}}]$$

$$+ \xi_1^{ols}$$

$$Y_0 = \beta_0' X_0 - \sigma_{\rho_0} \frac{\phi(z_1' r_1)}{1-\Phi(z_1' r_1)} + \{\xi_0 + \sigma_{\rho_0} \frac{\phi(z_1' r_1)}{1-\Phi(z_1' r_1)}\} = \beta_0' X_0 - \sigma_{\rho_0} \frac{\phi(z_1' r_1)}{1-\Phi(z_1' r_1)} + \xi_0^{ols}$$

Under these assumptions, it can be shown easily that the expected values of the conditional random errors ($E(\xi_0^{ols} \mid I = 1), E(\xi_1^{ols} \mid I = 0)$) are equal to zero. Consequently, the OLS estimation of equation (4.14) for each group yields consistent estimators for ($\beta_1, \beta_0, \sigma_{\rho_1}, \sigma_{\rho_0}$).

Estimating the Technical Efficiency Index

Rather than limiting our attention to a traditional production function to study the effects of CRP participation on farm productivity, we exploit the distinct advantage associated with a stochastic production frontier. Through this more complex specification, it is possible to calculate a technical efficiency index for each farmer.

Separate production functions for these two groups based on an appropriate formulation of the stochastic frontier function can be rewritten as:

(4.13) $Y_1 = \beta_1' X_1 + \xi_1 = Y_1^F + v_1 - u_1$

$$Y_0 = \beta_0' X_0 + \xi_0 = Y_0^F + v_0 - u_0$$

where the variables (Y_1^F, Y_0^F) are assumed to be the frontier production functions of each group, respectively. Following Aigner *et al.* (1977), we assume the random variable (v_i, for i = 0,1), a two-sided error term, has a normal distribution of *N*~(0, σ_{vi}^2). The random variable (*u*), a one-sided error term, is the non-negative technical efficiency component with a variance $\sigma_{ui}{}^{2}$. The two components are assumed independent. To implement the two stage method of moments, this involves estimated the traditional production functions first then decomposing the estimated error of the production functions (ξ_1, ξ_0) into two terms (v_1, u_1, v_0, u_0).

To proceed with the decomposition of this error structure, we must first recognize that the expected values of the two one-sided error terms (E(u_1) and E(u_0)) are not equal to zero. We can rewrite equation (4.13) as:

(4.14) $Y_1 = \beta_1' X_1 + \xi_1 = Y_1^F - E(u_1) + [v_1 - u_1 + E(u_1)]$

$$Y_0 = \beta_0' X_0 + \xi_0 = Y_0^F - E(u_0) + [v_0 - u_0 + E(u_0)]$$

From equation (4.14), two conditions must hold:

(4.15) $\beta_1' X_1 = Y_1^F - E(u_1)$ and $\xi_1 = [v_1 - u_1 + E(u_1)] = e_{scf1} + E(u_1)$

$$\beta_0' X_0 = Y_0^F - E(u_0) \quad \text{and} \quad \xi_0 = [v_0 - u_0 + E(u_0)] = e_{scf0} + E(u_0)$$

We can easily see that the parameters ($\sigma_{v1}^2, \sigma_{v0}^2, \sigma_{u1}^2, \sigma_{u0}^2$) can be calculated using the information about (ξ_1, ξ_0), if combined with the information about E (u_1), and E (u_0). Although the predicted values of ($\hat{\xi}_1, \hat{\xi}_0$) can be informed from equation (4.13), we must specify the distribution of (u_1, u_0) to have the necessary information about (E (u_1), E (u_0)).

Once the distributions of u_1 and u_0 are specified, we can obtain estimates of the parameters of interest ($\sigma_{v1}^2, \sigma_{v0}^2, \sigma_{u1}^2, \sigma_{u0}^2$) by utilizing the fact that since E (u_1) are E (u_0) are constant, the second and third central moments of ($\hat{\xi}_1, \hat{\xi}_0$) should be equal to the second and third central moments of (v_1-u_1) and (v_0-u_0). This amounts to applying the two-stage method of moments to estimate the stochastic production frontier (Byrnes 1991; Huang *et al*., 2002).[29]

[29] This method was first proposed by Byrnes (1991) who studied the effects of private versus public

Perhaps the best way to think about the estimation strategy for the stochastic production frontier is in two steps. In the first step, we estimate the traditional production functions for each group, ignoring technical efficiency. This is equivalent to estimating equation (4.11) from above by OLS. This provides consistent estimates of the parameters ($\beta_1, \beta_0, \sigma_{\rho_1}, \sigma_{\rho_0}$), as above. In step two, we decompose the predicted errors from the first step ($\hat{\xi}_1^{ols}, \hat{\xi}_0^{ols}$) into their two components (random shock and the technical inefficiency) and calculate the remaining parameters, ($\sigma_{v1}^2, \sigma_{v0}^2, \sigma_{u1}^2, \sigma_{u0}^2$).

Under the half-normal distribution, u_i is assumed to be $N^+(0, \sigma_{ui}^2)$. The first three moment conditions for u are:

(4.16) $$E(u_i) = \sqrt{\frac{2}{\pi}}\sigma_{u_i}$$

(4.17) $$V(u_i) = \frac{\pi - 2}{\pi}\sigma_{u_i}^2$$

(4.18) $$E(u_i^{\,3}) = -\sqrt{\frac{2}{\pi}}(1 - \frac{4}{\pi})\sigma_{u_i}^3 .$$

To solve for the parameters ($\sigma_{v_i}^2, \sigma_{u_i}^2$), we must recall the definitions of moments:

(4.19) $$m_2 = \sigma_{v_i}^2 + V(u_i) = \sigma_{v_i}^2 + \frac{\pi - 2}{\pi}\sigma_{u_i}^2$$

$$m_3 = E(u_i^{\,3}) = -\sqrt{\frac{2}{\pi}}(1 - \frac{4}{\pi})\sigma_{u_i}^3 .$$

The consistent estimators of ($\sigma_{v_i}^2, \sigma_{u_i}^2$) are then:

(4.20) $$\hat{\sigma}_{u_i}^2 = \left(\frac{m_3}{\sqrt{2/\pi}(1 - 4/\pi)}\right)^{2/3} \quad \text{and} \qquad \hat{\sigma}_{v_i}^2 = m_2 - (1 - \frac{2}{\pi})\hat{\sigma}_{u_i}^2 .$$

ownership on cost efficiency. Later, Huang *et al.* (2002) applied the similar approach to the case of rice cultivation in Taiwanese rice industry. In both papers, the analysis only focuses on the binary choice problem. Here, we extend and apply their approach to the sequential CRP choice problem.

Once the estimators of $(\sigma_{v_i}^2, \sigma_{u_i}^2)$ have been determined, the components of the two errors in the stochastic production frontier can be obtained as:

$$(4.21)\quad \hat{e}_{scf\,i} = \hat{\varepsilon}_i - \sqrt{\frac{2}{\pi}}\hat{\sigma}_{u\,i} \quad \text{and} \quad \hat{Y}_i^F = \hat{\beta}_i{}' X_i + \sqrt{\frac{2}{\pi}}\hat{\sigma}_{u\,i}\,.$$

Once the frontier model is estimated, the calculation of the technical efficiency index requires point estimates for the random variable *u* for each farmer. Following Jondrow *et al.* (1982), the expected value of *u* given the composite error (*v*-*u*) under the assumption of a half-normal distribution is:

$$(4.22)\; E(\hat{u}_i \mid \hat{e}_{scfi}) = \frac{\sigma\lambda}{(1+\lambda^2)}\left[\frac{\phi\left(\frac{\hat{e}_{scfi}\lambda}{\sigma}\right)}{1-\Phi\left(\frac{\hat{e}_{scfi}\lambda}{\sigma}\right)} - \frac{\hat{e}_{scfi}\lambda}{\sigma}\right],$$

where $\sigma = (\hat{\sigma}_{u_i}^2 + \hat{\sigma}_{v_i}^2)^{1/2}$ and $\lambda = \frac{\hat{\sigma}_{u_i}}{\hat{\sigma}_{v_i}}$.

Once these conditional expected values are obtained, the technical efficiency index of each farmer can be calculated as (Kumbhaker and Lovell, 2000):

$$(4.23)\quad TE = e^{-E(\hat{u}|\hat{e}_{scf}\,i)}$$

Estimating Productivity Differences between Groups

One of the main objectives of this study is to examine the farm productivity differences between groups of farmers to understand how CRP participation affects productivity or efficiency. We cannot directly compare the technical efficiency indices from the estimation above because the production environment is assumed to differ by group. However, the above results do provide information on differences in technical efficiency for farms within each group. Using this information, we can estimate the Total Factor Productivity (TFP) index proposed by Malmquist (1953) to see the relative productivity differences between groups based on the sample mean of each group.[30] Using this approach, we can not only see the differences in TFP, but also identify the sources of the differences by decomposing TFP into *relative* differences in scale efficiency and the *relative* differences in technology.[31]

Although non-parametric data envelope analysis (DEA), where the TFP index is based on the distance function, is normally applied along with the Malmquist TFP Index, TFP can also be defined using stochastic production methods (Coelli *et al*., 1998). Therefore, we consider non-participants (regime A3 of Figure 4.1) as the base group, and use the generalized version of the TFP formula outlined by Coelli (2003) and Lovell (2003):[32]

$$(4.24) \quad M(y_1,x_1,y_0,x_0) = \underbrace{\frac{TE^{V1}(y_1,x_1)}{TE^{V0}(y_0,x_0)}}_{(T.C)} * \underbrace{\left[\frac{TE^{V0}(y_0,x_0)}{TE^{V1}(y_1,x_1)}\frac{TE^{C1}(y_1,x_1)}{TE^{C0}(y_0,x_0)}\right]}_{(E.C)}.$$

$$* \underbrace{\left[\frac{TE^{C0}(y_1,x_1)}{TE^{C1}(y_1,x_1)} * \frac{TE^{C0}(y_0,x_0)}{TE^{C1}(y_0,x_0)}\right]^{1/2}}_{(frontier)},$$

where M(.) represents the relative TFP index of group 1 (Partial CRP participants) relative to group 0 (non-participants). V and C superscripts refer to the variable returns

[30] Although the TFP index is usually applied to time series data to measure productivity changes through time, this concept can also be applied to the cross section data. In some resent studies, researchers have applied this approach to make cross-country comparisons in efficiency (Fare *et al*., 1994; Thirtle *et al*., 1995; Fulginiti and Perrin, 1997) and make comparisons for different age groups (Tauer and Lordkipanidze, 2000).

[31] Goodwin and Mishra (2004) define the efficiency index or productivity index as the total value of output value divided by the total value of inputs. This index number approach explores little information about the sources of the productivity differences (Kumbhaker and Lovell, 2000).

[32] The conventional version of TFP index proposed by Fare et al. (1994) is:

$$M(y_1,x_1,y_0,x_0) = \frac{TE^1(y_1,x_1)}{TE^0(y_0,x_0)} * \left[\frac{TE^0(y_1,x_1)}{TE^1(y_1,x_1)} * \frac{TE^0(y_0,x_0)}{TE^1(y_0,x_0)}\right]^{1/2}$$

In this version, the total factor productivity can only be decomposed into two components: technical efficiency and technology. However, the generalized version we use in this study can accommodate not only two sources of total factor productivity, but also the scale efficiency.

to scale (VRS) and constant returns to scale (CRS) production functions, respectively. If $M > 1$, the TFP of group 1 is greater than that for group 0; we can infer that partial CRP participation increases TFP. The term $TE^{kj}(y_i,x_i)$ represents technical efficiency for group j using the level of inputs for group *i*. Total factor productivity is decomposed into three sources. The ratio outside the square brackets (refer to *T.C*) measures the relative difference in technical efficiency between groups 1 and 0, which actually measures the relative distance between actual production and the frontier function between groups for the VRS technology. The first term in brackets (refer to *E.C*) measures the ratio of scale efficiencies between groups.[33] The second term in brackets (refer to *frontier*) measures the relative difference in technologies, which is the comparison of the production frontiers between groups. If this term is greater than one, the production frontier of group 1 lies above that for group 0. If this is the case, the production frontier might be higher for farms participating in CRP participation.

Empirical Results

As is apparent in the discussion of the econometric methods, we distinguish several sets of results. The results for the sequential CRP choice model and the specification tests are reported in Tables 4.1 and 4.2. The estimated equations for the CRP payment and acreage are reported in Tables 4.3 and 4.4, respectively. We report the estimated production functions and the estimates of the technical efficiency functions in Tables 4.5-4.7, respectively. Finally, the related measures of technical and economic scale efficiency and productivity are shown in Tables 4.8. Throughout the discussion of these results, the effects of variables on CRP participation, CRP

[33] Scale efficiency is measured as the amount by which productivity can be increased by moving to the point of technical optimal productive scale (Coelli 1998). In general, scale efficiency measures the effect whether firms are operating in the optimal size. In this study, we are interested in measuring the difference that how the partial CRP and non-CRP participants utilize the technology to their optimal productive scale.

payments, and CRP acreages are obvious from the signs on particular variables. Therefore, to avoid unnecessary repetition and in an attempt to make the discussion more conversational, we describe the results in general terms.

From Table 4.1, the correlation coefficient between CRP participation and the partial CRP farm decision is very high (0.68), and it is also statistically significant at 5% or higher level. We also test the hypothesis to see if the CRP participation and partial CRP farm decision can be regarded as two independent sequential decisions.[34] The likelihood ratio test value is 34, which is higher than the critical value under 5% level ($x^2(0.95,1)=3.84$). This result immediately shows that it is appropriate to consider CRP participation and the partial CRP farm decisions as a dependent choice structure, rather than two independent sequential decisions.

[34] If these two sequential decisions are assumed to be independent, the correlation coefficient is zero. This constructs the restricted model for likelihood ratio test.

Table 4.1: Sequential Choice Equations

Variable	Coefficient	Std	b/Std
		CRP Choice Equation	
Constant	-5.905	1.342	-4.400
OP_AGE	0.034	0.003	9.907
OP_ED_C	0.065	0.016	4.044
RISK	-0.064	0.018	-3.643
OP	0.272	0.091	2.978
EBI	0.057	0.020	2.787
LQH_96	0.390	0.190	2.049
LQL_96	-1.157	0.335	-3.448
AGDIST	-1.130	0.267	-4.229
AMTA_A	-0.035	0.004	-8.158
CROP456	-1.806	0.240	-7.539
CROPSIZ1	0.265	0.039	6.853
REGN567	-0.362	0.143	-2.521
REGN9	1.240	0.256	4.848
URBAN	-0.013	0.002	-7.132
		Partial CRP Choice Equation	
Constant	-3.638	0.817	-4.451
OP_RET	-1.494	0.370	-4.041
OP_EXP	0.020	0.006	3.501
OP	-0.571	0.295	-1.934
RISK	0.154	0.046	3.346
LQH_96	1.679	0.388	4.331
DEBT_RAT	1.286	0.557	2.309
CROPSIZ1	0.250	0.063	3.957
AGRIN	-0.020	0.017	-1.186
MANUF	-0.025	0.016	-1.600
TRADE	0.108	0.037	2.898
REGN2	-1.293	0.411	-3.144
		Correlation Coefficient	
RHO	0.682	0.144	4.731
Sample	2,223		
LogL	-946		
LR Test*	34		

* *The critical value of* $x^2(0.95,1)=3.84$

Variable definitions are listed in Table 2.4 of Chapter 2.

CRP Participation Equation

The empirical results of the CRP participation equation (the top proportion of Table 4.1) are encouraging, and are generally consistent with our household production theory. Participation depends generally on some characteristics of the farm, the farm operator, land quality and the circumstances in the local economy. There are also some differences in participation by major ERS production region.

Based on these results, the propensity of participation in CRP increases with farm size;[35] the propensity of CRP participation is lower if the farm is primarily engaged in vegetable, fruit or nursery production, rather than cash grain production. This finding is not unexpected because of the high production value from the vegetable or nursery farming, which reflects the higher opportunity cost for those specific farmers to enroll their lands in CRP. It is also perhaps no surprise that the receipt of decoupled payments decreases the likelihood of participation in CRP, since the farmland must remain in production in order to receive decoupled payments. However, the opposite is true if there is land on the farm that is: enrolled in a voluntary agricultural district, subject to a farmland preservation easement, or located in an agricultural protection zone or zoned exclusively for agricultural use. Farms located in agricultural districts generally wish to maintain their land in agricultural production, although many districts are in rapidly growing areas where there is competition for land for non-agricultural purposes. Therefore, it is hardly surprising that, *ceteris paribus*, these farmers would be less likely to enroll land in a program such as CRP that essentially takes land out of production. Another interesting finding is that farm households located in the higher EBI score areas have a higher propensity

[35] The effect of farm size on CRP differs in the empirical literature. Konyar and Osborn (1990) found the negative correlation between farm operating acreage and CRP participation based on county level data; while Mclean, Hui, and Joseph (1994) surveyed 113 farmers in Louisiana and found a positive relationship.

for CRP participation. Our finding is consistent with Isik and Yang (2004) and Park and Schorr (1997).[36] The reasonable explanation might be reflected in the fact the bidding process, since higher EBI scores are the points assigned to a farm household bid, thus increasing the likelihood that the bid is accepted. Thus, in a very general way, this result is consistent with the actual implementation of the program in with contracts are accepted in large measures on the EBI ranking.

Three measures of soil quality in the surrounding area were constructed to determine if participation in CRP was related to the quality of the soil resource. Based on these measures, participation in CRP rises as the proportion of land in the surrounding county is classified as high quality. The probability of participation falls as the proportion of low quality of land rises. This result might suggest CRP participation may be higher in areas where land is well suited for agriculture. Unfortunately, unless one had information about land quality by farm, it would be impossible to tell anything about the quality of land that is actually enrolled in CRP, or how the land quality on the farm affects a farmer’s decision to participate. However, our finding is not inconsistent with those who found the negative relation between soil erosion index and CRP participation based on the county level analysis (Goodwin, Vandeveer, and Deal (2004); Konyar and Osborn (1990)).

The effects of the operator’s human capital (age and education) on CRP participation vary in the literature.[37] In our analysis, two variables suggest participation in CRP is related to the life cycle and human capital of the farm operator. The likelihood of CRP participation increases with the level of operator’s age and

[36] Park and Schorr (1997) defined the maximum bid price as one of the factors affecting CRP participation. Their finding are not be directly compared to our result. However, maximum bid price is determined based on EBI score. One might expect that these two measures are highly correlated.

[37] Konyar and Osborn (1990) and Kalaitzandonakes and Monson (1994) both found a negative relationship between age and the CRP participation. However, McLean, Hui, and Joseph (1994) found the reverse.

education. As the farm operators get older, committing some land to CRP may be one way of reducing operator labor requirements. This may also be a way of holding onto farmland assets until they are needed for the retirement years, or so that they can be passed on through an estate. The fact that the operator of the farm household working off the farm are more likely to participate in CRP may also be a way of reducing farm household labor requirements. Finally, it is likely that CRP payments are less variable from year-to-year than are returns to farming activity. Therefore, it is not surprising to see that the probability of CRP participation falls as a farmer's preference for risk increases. The fact that the likelihood of CRP participation falls as the proportion of population that is urban rises would seem to reinforce this explanation.[38]

Whole or Partial CRP Farm Participation

The factors that distinguish between the partial (or whole) CRP participants are operator's characteristic, farm size, government payment, and the economic location (the bottom section of Table 4.1). The operators who are retired from farming are less likely to be partial CRP participants. This result certainly reinforces the hypothesis that older farmers participate in CRP in part to pass farm assets through an estate, and CRP payments can be an important supplant to retire income. It is also true that this effect is also explained by the fact that the farmers with more farming experience, large farms or with high debt to asset ratios are more likely to be partial CRP participants. Furthermore, once the decision to participate in CRP is made, partial CRP participation is less likely for more risk averse farmers. Farm operators who work off the farm are also more likely to the whole CRP participants. For those farmers, there is a significant incentive to reduce the land commitment to agricultural production, particularly for those with full time jobs off the farm.

Finally, the local and regional economic conditions determine the partial CRP

[38] Duke (2004) also found that the likelihood of participation in CRP is lower in highly urban areas.

farms participation. If the local economy depends less on manufacturing or is more dependent on wholesale and retail trade, CRP participation is more likely to be partial.

Exogeneity Tests of the Sequential CRP Choice Model

In models such as these, there is always concern that variables related to other decisions by members of the household are endogenously determined, in this case determined along with the decision to participate in CRP (first stage choice). Therefore, before leaving our discussion of the sequential CRP participation model, it is important to address the issue of whether or not these other binary choices specified in these two choice equations are exogenous to the binary CRP or partial CRP choices. The results of these tests clearly affect the validity of any policy conclusions involving these variables.

The variables for which this is a concern in this study are related to: off-farm work by the operator, participation in agricultural districts or related farmland retention activities, and the receipt of decoupled payments. In the model, the first two of these decisions are treated as binary choices, while the last is modeled as a continuous variable. For the partial or whole CRP farm participation decision (second stage choice), the tested variables are: off-farm work by the operator, retire decision of the operator, the risk preference of the operator, and the retirement decision of the operator. The two variables are treated as the binary choice variables.

For each of these variables, we test the null hypothesis that these decisions are exogenous to CRP or partial CRP farm decisions. We test the null hypothesis that these decisions associated with two discrete binary variables are exogenous to CRP participation and two variables to partial CRP farm decisions using a method by Vella (1993). The tests for the binary variables are slightly different than for the continuous variables. For the continuous variable, the test is based on methods by Smith and Blundell (1986).

These tests involve several steps. For the discrete variable cases, the first step is to specify separate participation equations for those variables involved in the tests. There are two sets of explanatory variables included in these additional participation equations: the first set includes the variables we have specified in the CRP participation equation; the second set includes some new variables that are believed to determine the variable on which the test is being conducted.[39]

Once these additional participation equations are specified, we estimate four separate two-equation simultaneous probit models using the method proposed by Vella (1993).[40] Each two-equation system includes the original CRP equation, plus a second equation representing one of the variables to be tested. For each simultaneous probit model, we calculate the general residuals for the new participation equations from the estimated parameters. Next, we re-estimate the original binary CRP equation by including the general residual as a new explanatory variable. If the t-ratios on coefficients associated with the general residuals now included in the original binary CRP equations are statistically insignificant, then we fail to reject the hypothesis that these binary choices are exogenous.[41]

A similar procedure is applied to the continuous variable case (e.g., decoupled payments).[42] Once the new equation is specified, we follow the two-stage method proposed by Smith and Blundell (1986) to test the null hypothesis that decoupled payment are exogenous to the two-equation system. We can calculate the predicted values for decoupled payments. These predicted values are added to the original CRP

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[39] The specification of these extra variables is based on the goodness of fit from several possible trials.
[40] Empirically, the additional variables used in testing the operator's decision to work off the farm and the retirement decision are: if the operator is raised on the farm and indices relating to the local economic importance of manufacturing, services, agriculture, and trade.
[41] Vella (1993) did not derive the asymptotic property for the standard error of the coefficient. Alternatively, we adjust the standard error based on the asymptotic theory proposed by Murphy and Topel (1985).
[42] Empirically, the additional variables we specify in testing the decision to receive decoupled payments decision are the local economic indices for manufacturing, agriculture, services, and trade.

binary choice model as a new explanatory variable; the model is re-estimated, and if the coefficient on this new variable is statistically insignificant, then we fail to reject the null hypothesis that decoupled payments are exogenous.

We report the results of these tests of the null hypotheses that these variables are exogenous to the CRP probit model or partial CRP farm decisions in Table 4.2, and they are encouraging. In all cases, we fail to reject the hypothesis that the corresponding decision is exogenous to the decision to either participate in CRP or partial CRP farm.

Table 4.2: Exogeneity Test

Variables	T Value	P-Value
	For CRP Choice Equation	
OP	-0.225	0.822
AGDIST	0.920	0.358
AMTA_A	0.789	0.430
	For Partial CRP Equation	
OP	-0.034	0.973
OP_RET	0.092	0.927

Variable definitions are listed in Table 2.4 of Chapter 2.

Second Stage Equations

In developing a complete understanding of factors affecting CRP enrollment, we must also estimate an equation for the number of acres enrolled for the CRP participants. Since it is expected that the level of payment may influence the amount of land enrolled, we estimate a CRP per acre payment equation as well. These results are reported in Tables 4.3 and 4.4, respectively. As noted above, the inverse mills ratios are included in both equations to control for any sample selection bias, and it is statistically significant in both. Further, consistent with a tradition for specifying wage equations in the labor economics literature, the performance of the payment equation was improved through a semi-logarithmic specification (e.g., the dependent variable is the logarithm of CRP payments).

Table 4.3: CRP Payment Equations

Variable	Coefficient	Std	b/Std	Coefficient	Std	b/Std
	For Partial-CRP Farm			**For Partial CRP Farm**		
CONSTANT	2.593	0.502	5.161	2.075	0.244	8.492
OP_EXP	0.042	0.010	4.266	0.042	0.010	4.236
OP_EXPSQ	-0.001	0.000	-4.684	-0.001	0.000	-3.222
H_SIZE	-0.050	0.032	-1.567	-0.014	0.052	-0.277
AGDIST	-0.220	0.391	-0.563	-1.543	0.375	-4.119
CROP456	-0.664	0.554	-1.198	--	--	--
LQH_96	1.534	0.248	6.182	0.719	0.191	3.757
LQM_96	0.988	0.351	2.815	1.102	0.476	2.316
REGN1	--	--	--	0.532	0.121	4.410
REGN567	-0.437	0.145	-3.019	-0.678	0.340	-1.995
MANUF	0.020	0.007	2.767	0.022	0.004	5.127
TRADE	-0.017	0.019	-0.880	--	--	--
IMR_CRP	0.271	0.105	2.572	0.422	0.171	2.460
IMR_WP	0.292	0.117	2.489	0.242	0.204	1.184
Wald Test*	7.71			11.28		
Sample	288			109		
Adjust-R^2	0.361			0.616		

* *The critical value of x^2 (0.95,2)=5.99; x^2 (0,90,2)=4.61*
Variable definitions are listed in Table 2.4 of Chapter 2.

<u>The CRP Payment Equation</u>

Table 4.3 reports the results for CRP payment equations of both partial CRP and whole CRP farms. The Wald test results (7.71 and 11.28, respectively) for testing whether the Inverse Mills Ratios are jointly equal to zero show the importance of the self-selection problem. In both cases, the test results are statistically significant. Since the effects of the explanatory variables are similar for both groups, we discuss the results in general below.

On balance, the factors that affect the size of CRP payments make sense. CRP payments are directly related to the proportion of land in the area that is of high quality, and payments differ by region. All else equal, they tend to be higher in the Heartland, but lower in the Eastern Uplands, the Southern Seaboard, and the Fruitful Rim than in the rest of the ERS production regions.[43] Payments increase with the percentage of local employment in manufacturing, which, in turn, is likely to be related to the strength of the regional economy.

The CRP payment also decreases as the proportion of land on the farm that is planted to vegetable, fruit or nursery increases, which might well reflect the fact that these farm operators may tend to enroll somewhat poorer quality land in CRP, particularly in situations where the most productive land is retained in cash crop production.

The effect of human capital on payment is represented by years of farming experience and its squared term. The farmer with more farming experience is likely to receive higher payments, but the payment increases at a decreasing rate. This experience may well contribute to these farmers' effectiveness at bidding and selecting the most appropriate land to enroll and management practice used on the CRP land.

The CRP Acres Equation

Because it is likely that CRP payments and acreage enrolled are endogenously determined, we use the predicted per acre payment instead of the observed per acre payment as the instrument for payment variable in the CRP acreage equation.[44] From a policy standpoint, the factors that affect the acreage enrolled in CRP as partial or

[43] While these results would seem reasonable, it would be helpful to know how these differences square with differences in agricultural land prices or rental rates across these regions. If this were true, then there would be some evidence that CRP payments differ in relation to the opportunity cost of land in agricultural production by region.
[44] This strategy is commonly used in labor economics (Killingsworth, 1983 and Fernandez, Rodriguez and Sperlich, 2001).

whole CRP farms are quite interesting (Table 4.4).[45]

From Table 4.4, it appeals that land acre enrolled increases with the payment per acre (P_HAT). The effect is greater for the partial CRP farm participants, and this effect is statistical significant in this equation as well. One would certainly expect acreage enrolled to respond to this direct payment incentive.[46] It is perhaps one of the most significant findings in our analysis because it is inconsistent with much of the previous literature, particularly studies based on county-level analysis, where the acres enrolled fall as payments rise.[47]

Although the number of acres enrolled in CRP increases as the CRP payment per acre increases, the negative coefficient on an interaction term for payment and low land quality (PLQL) indicates that this effect decreases in areas with higher proportions of low quality land. The CRP acre responses to CRP per acre price are depicted in Figures 4.2 and 4.3 for partial CRP farm and whole CRP farms, respectively. Accounting for the low land quality index, we find that the overall price effects are different between partial and whole CRP farms. For the whole CRP enrollees, the overall price effect is negatively response to low land quality of the sample, but the overall price effect is positively response to the lower proportion of the low land quality. The fact that the positive price effect decreases in areas with high proportions of low quality land is consistent with the belief held by some that the maximum payment is often set too high in areas attempting to enroll higher quality

[45] The Inverse Mills Ratios are included in both equations to control for any sample selection bias, and they are statistically significant in both. The Wald test results to test whether the two Inverse Mills Ratios are jointly equal to zero are 27.25 and 7.26, respectively, which are statistically significant at 5% or higher level.

[46] Suter (2004) found that annual incentive payments affect CREP enrollment in buffer strips, measured as a proportion of eligible farmland. His study is based on data aggregated at the county level, but the positive relationship between land enrolled and level of payment was only apparent when he used a refined estimate of eligible farmland derived from GIS data on the amount of agricultural land along streams in the target watersheds.

[47] For example, both Fleming (2004) and Goodwin *et al*. (2004), who study the CRP acreage response based on the county-level data, found a negative relationship between CRP acreage enrollment and the annual payment.

Table 4.4: CRP Acre Equations

Variable	Coefficient	Std	b/Std	Coefficient	Std	b/Std
	For Partial-CRP Farm			**For Whole-CRP Farm**		
Constant	705.676	355.706	1.984	1180.909	669.001	1.765
OP_AGE	–	–	–	-1.790	2.677	-0.669
OP_ED_C	76.730	44.471	1.725	2.380	97.162	0.024
OP_EDSQ	-2.845	1.661	-1.713	-0.973	3.590	-0.271
OP_EXP	-4.471	1.967	-2.273	–	–	–
CROP17	53.370	55.045	0.970	–	–	–
AMTA_A	3.309	2.589	1.278	-11.408	12.710	-0.898
NETWORT1	3.756	1.715	2.190	5.937	35.299	0.168
TENANCY	-3.037	6.676	-0.455	-21.637	14.401	-1.502
LQH_96	-999.010	311.566	-3.206	-776.991	409.275	-1.898
LQM_96	-722.776	268.155	-2.695	-536.224	452.445	-1.185
EQIP	21.869	114.393	0.191	-422.721	149.321	-2.831
REGN1	-79.167	42.118	-1.880	–	–	–
REGN3	-68.444	110.067	-0.622	162.854	108.431	1.502
REGN9	–	–	–	-179.874	127.996	-1.405
TRADE	-1.996	13.885	-0.144	-7.025	14.829	-0.474
PLQL	-15.489	5.319	-2.912	-13.448	12.821	-1.049
P_HAT	2.085	1.082	1.926	1.424	2.538	0.561
IMR_CRP	-223.497	117.828	-1.897	-213.480	124.886	-1.709
IMR_WP	-221.913	103.311	-2.148	-195.834	116.261	-1.684
Wald Test*	27.25			7.26		
Sample	288			109		
Adjust-R^2	0.335			0.421		

* *The critical value of x^2 (0.95,2)=5.99; x^2 (0,90,2)=4.61*
Variable definitions are listed in Table 2.4 of Chapter 2.

land. It is also consistent with a belief that some farmers, who try to enroll poorer quality land into CRP, bid relatively low to ensure acceptance, thus resulting in the negative price response. This is supported by our analysis for the whole farm participants. It is not surprising that the effect of price becomes negative in areas with lower proportion of poor quality land than for partial CRP participants.

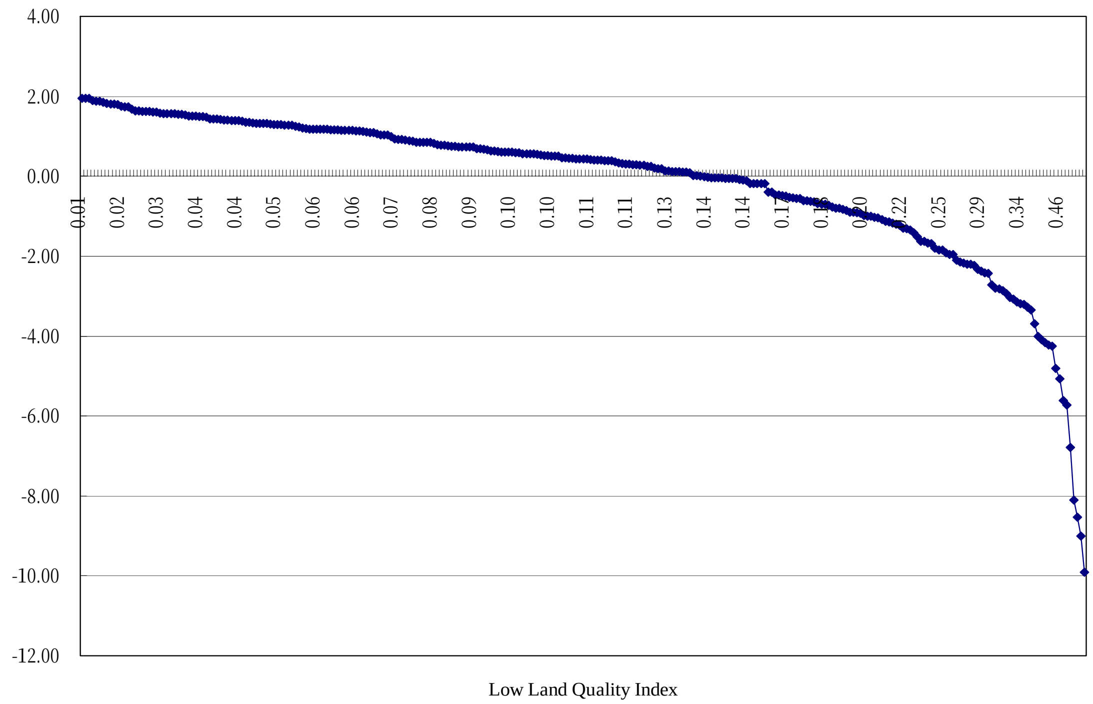

Figure 4.2: CRP Acre Response to CRP Per-Acre Price (Partial CRP Farm)

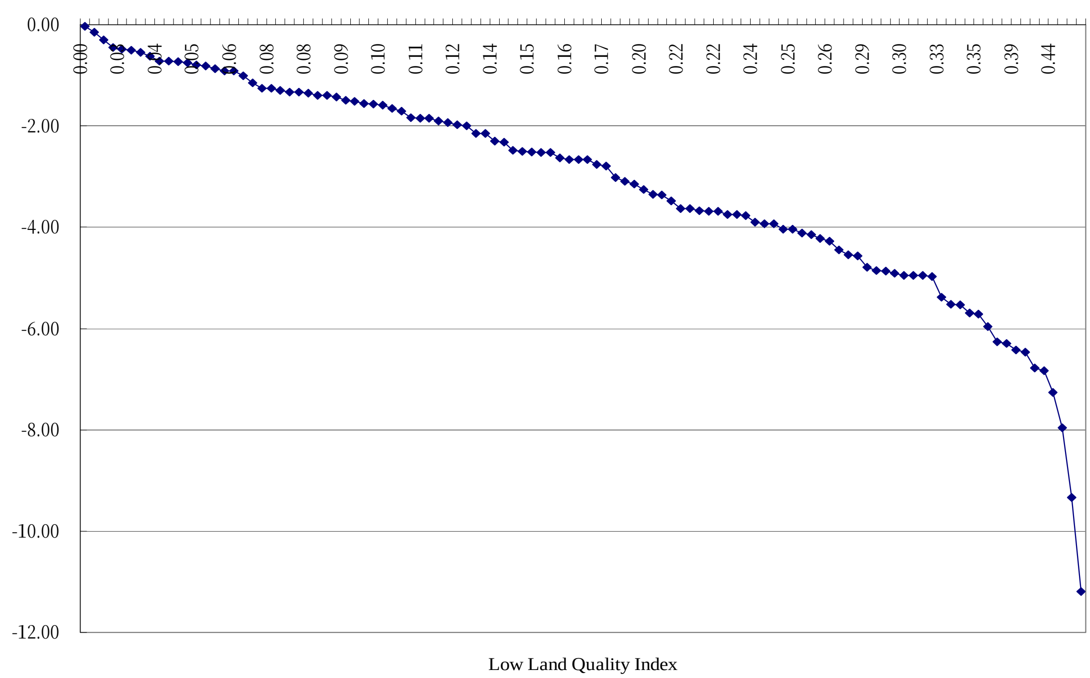

Figure 4.3: CRP Acre Response to CRP Per-Acre Price (Whole CRP Farm)

There are also substantial differences in the CRP acreage by region. Acreage enrolled is lower in the Heartland and Mississippi Portal, but higher in the Northern Great Plains, Eastern Uplands, the Southern Seaboard, and the Fruitful Rim. Given that much of the best farmland in the country is in the Heartland, these results reinforce the fact that acres enrolled for CRP participants decline as the proportion of land that is of high quality in a locality increases. This is somewhat at odds with the results from the CRP participation equation (Table 4.1), where the likelihood of participation in CRP is increased as the proportion of land that is of high quality in a locality increases. However, our result might be interpreted as a problem in adverse selection: farmers may be unlikely to enroll high or medium quality land into CRP; they retain it in crop production. It is difficult to know if this finding is consistent with one of the primary goals of CRP, the reduction of soil erosion and other environmental residuals associated with agricultural production. There is consistency only if it is the poorer quality land that is more subject to erosion and more environmentally venerable.

CRP acreage enrollment is also affected by local economic indices. Local areas with a higher proportion employed in manufacturing have less land enrolled in CRP, which might reflect the opportunity cost of land in non-agricultural uses and work against large acreages being committed to programs such as CRP.

There are also characteristics of the farming operation and households that affect the acreage enrollment. Acreage enrolled increases for those farms classified as cash grain farms, although the effect is not statistically significant in the acreage equation. Acres enrolled decrease with the farming experience of the farm operator but increase with the farm operator’s level of education in a nonlinear faction; this reinforces the effect from the participation equation.

Production Function and Farm Productivity

As introduced above, we next identify the effect of CRP participation by first estimating two separate production functions, one for CRP participants and one for non-participants. In order to decompose the economic efficiency, we estimate two production function of each group based on variable return to scale and constant return to scale technologies. The second step is to estimate the technical efficiency of each farm household by decomposing the compound error on the frontier function into technical efficiency and random shock components. Given the estimated technical efficiency by groups and utilizing Malmquist Total factor Productivity Index (1953), we compare the different performance regarding technical and scale efficiencies, production frontiers, and total factor productivities of two groups. The comparison is based on the sample means of each group. Finally, given the estimated technical efficiency, we are able to discuss the factors determining the technical efficiency index of each group and the heteroscedasticity between groups.

The Production Function

To perform this analysis, we specify two Cobb-Douglas production functions, one for partial CRP farms and one for non-participants.[48] All of the output and input variables are specified in logarithm. Gross cash sales is used as the measure of production, while there are four inputs, operating land (LGLAND), variable production cost (LGLC_C), hired labor cost (LGLABOR), and capital (LGCA).[49] We aggregate the expenditures for fertilizer, seeds, plants, fuel, and utilities as a measure of the variable production cost. The hired labor cost includes regular hired labor and contact labor. Capital use is measured by the fixed value of building and farm

[48] When translog production functions are specified, the estimated input elasticities in the mean level are negative for some inputs. As such, we specify two Cobb-Douglas production functions here.
[49] The output variable we used here is the same definition as Goodwin and Mishra (2004), who study the efficiency impact of farm households working off-farm decision.

equipment, excluding dwelling value. The estimates of two separate production functions are shown in Table 4.5 and Table 4.6. However, we focus on the variable return to scale estimation for further analysis (Table 4.5).

Table 4.5: Production Function Estimation (Variable Returns to Scale)

Variable	Coefficient	Std	b/Std	Coefficient	Std	b/Std
	For Partial-CRP Farm			**For NON-CRP Farm**		
Constant	-4.373	0.578	-7.563	-4.778	0.270	-17.726
LGLAND	0.426	0.099	4.299	0.254	0.033	7.609
LGLC_C	0.262	0.087	3.006	0.495	0.049	10.088
LGLABOR	0.085	0.020	4.284	0.113	0.009	12.435
LGCA	0.349	0.090	3.882	0.198	0.033	5.945
IMR_CRP	0.131	0.072	1.820	0.193	0.098	1.967
IMR_WP	-0.549	0.181	-3.040	--	--	--
RTS	1.122			1.061		
Wald Test*	63.98			–		
Sample	308			1,740		
Adjust-R^2	0.726			0.717		

* *The null hypothesis of Wald Test is: IMR_CRP=IMR_WP=0;*
The critical value of x2(0.95,2)=5.99; x2(0,90,2)=4.61

Table 4.6: Production Function Estimation (Constant Returns to Scale)

Variable	Coefficient	Std	b/Std	Coefficient	Std	b/Std
	For Partial-CRP Farm			**For NON-CRP Farm**		
Constant	-3.547	0.244	-14.519	-4.491	0.098	-45.678
LGLAND	0.398	0.068	5.879	0.240	0.021	11.177
LGLC_C	0.266	0.048	5.490	0.495	0.020	24.875
LGLABOR	0.085	0.016	5.218	0.116	0.007	15.454
LGCA	0.251	0.061	4.118	0.149	0.021	6.988
IMR_CRP	0.111	0.101	1.099	0.097	0.101	0.965
IMR_WP	-0.670	0.134	-5.008	--	--	--
RTS	1.000			1.000		
Sample	308			1,740		
Adjust-R^2	0.718			0.715		

** The null hypothesis of Wald Test is: IMR_CRP=IMR_WP=0;*
The critical value of x2(0.95,2)=5.99; x2(0,90,2)=4.61

In Table 4.5, the coefficients of both functions on the Inverse Mills Ratio are statistically significant. The Wald test for joint Inverse Mills Ratios of the partial CRP farm group is 63.98, which is significant at the 5% level or higher. The t-value of the Inverse Mills Ratios of the non-CRP participant group is 1.967, which is also significant at the 5% level. Both of the results show it is necessary to consider the self-selection problem of the production function estimation.

It is also interesting to see that economies of scale in production are quite different between these two groups. Although the production functions for both groups exhibit increasing return to scale, farmers participating in CRP as the partial farms enjoy the higher economies scale (1.122 vs. 1.061). This result is not so surprising since the farm sizes of CRP participants are indeed larger than the non-CRP participants. The production elasticities for the inputs differ between groups as well.

Technical Efficiency and Productivity Comparison

In order to identify the effects of CRP participation on technical efficiency, it is necessary to compare the performance between groups. After decomposing the error structures for frontier production functions for these two groups using the two-stage method of moments described in equations 4.13 through 4.24, we utilize the Malmquist TFP Index formula to estimate differences between groups, in terms of total factor productivity, technical and scale efficiencies, and production frontiers. All of these comparisons in Table 4.7 are based on the mean levels of each group. At the means of the data, the total factor productivity of the group of partial CRP participants appears to be slightly below that of the non-participant group; the ratio of the two total factor productivities is 0.981. This is partially explained by the fact that the CRP participants also appear to be less technically efficient than the non-participants. The ratio of the technical efficiency indices between partial CRP participants and non-participants is 0.648. In determining the difference in TFP, this large difference in technical efficiency is offset by two other factors. First, the production frontier for the partial CRP participants is slightly above that for the non-participants; the ratio of these two frontiers is 1.15. Second, the partial CRP farms operate their firms closer to their technically optimal productive scales than the non-CRP participants. The ratio of scale efficiencies between these two groups is 1.317.

Table 4.7: Productivity and Efficiency Comparisons

Technical Efficiency, CRP participants (VRS)	0.238
Technical Efficiency,non-participants (VRS)	0.367
Technical Efficiency, CRP participants (CRS)	0.310
Technical Efficiency,non-participants (CRS)	0.364
Technical Efficiency, TE1C(0)	0.474
Technical Efficiency, TE0C(1)	0.535
Technical Efficiency Index Ratio	0.648
Production Frontier Index Ratio	1.150
Scale Efficiency Index Ratio	1.317
Total Factor Productivity Index Ratio	0.981

** Note: Ratios are calculated based on non-participant group.*
TE1C(0) is used the non-participants' data to match CRS1
TE0C(1) is used the CRP participants' data to match CRS0

Determinants of Technical Efficiency

To further understand the difference in terms of technical, scale efficiencies and farm productivity between these two groups, it is crucial to understand the factors determining these measurements of each group. We only focus on the technical efficiency equation to discuss the factors determining the technical efficiencies of each group. [50]

Given production function estimates of the two groups based on the variable return to scale technology (VRTS), the technical efficiency index of each farm household within the each group, can be estimated based on the two-stage method of moment approach outlined above. The distribution of the technical efficiency

[50] Ideally, it is necessary to discuss the factors determining not only technical efficiency but also scale efficiency of each group in order to explore the reasons of the differences between groups. However, our approach is not suitable to estimate the scale efficiency equation, since to calculate the scale efficiency requires the comparison of these two groups (see equation 4.24). As such, the scale efficiency index of each farm within each group is not available.

estimates for the groups are depicted in Figure 4.4 and Figure 4.5. The distributions of the technical efficiency of both groups are quite different. The estimated technical efficiency index is for the non-CRP participants are more centralized compared to the partial CRP farm group. Given the estimated technical efficiency index of each farmer as the dependent variable, OLS regression is applied to estimate technical efficiency index for both the partial CRP farms and the non-CRP participants to a number of social economic factors (Table 4.8). For each group, the factors determining the technical efficiency are farm and farm household characteristics, government policy, operator's characteristics, and environmental features.[51]

[51] Use of a second stage regression model to determine the factors the farm specific attributes in explaining technical efficiency have been suggested in a number of studies (e.g. Wadud and White 2000; Shafiq and Rehman 2000). Although some authors (Battese and Coelli 1995) proposed the one-step approach (*ie.* specify the social characteristics explaining technical efficiency to stochastic production model and estimate it with MLE) to improve efficiency of the technical efficiency equation, this method can't be applied to our study since the sequential CRP choice decision will complicate the MLE procedure of the stochastic production frontier model.

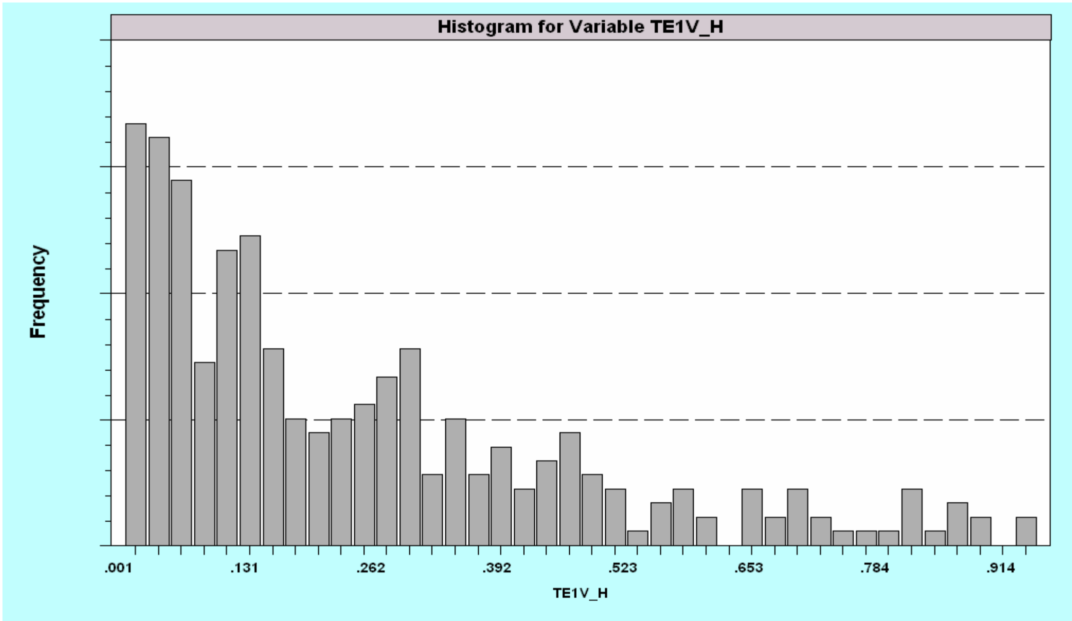

Figure 4.4: Distribution of the Estimated Technical Efficiency Index for Partial CRP Farm

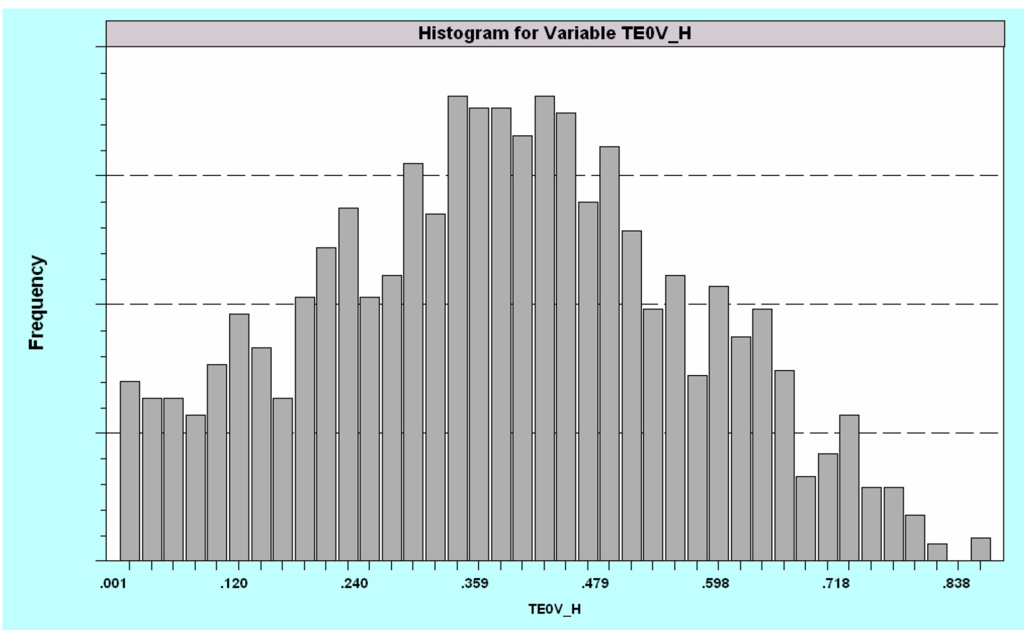

Figure 4.5: Distribution of the Estimated Technical Efficiency Index for Non-CRP Participants

Table 4.8: OLS Estimation of Technical Efficiency Equations

Variable	Coefficient	Std	b/Std
	FOR PARTIAL CRP FARM		
Constant	0.300	0.119	2.531
OP_AGE	-0.007	0.002	-3.514
OP_ED_C	0.005	0.005	1.165
AMTA_A	0.003	0.001	2.250
OP_EXP	0.004	0.003	1.416
OP_EXPSQ	0.000	0.000	-0.520
RAISE_OP	0.004	0.037	0.106
TENANCY	0.037	0.008	4.508
H_SIZE13	0.040	0.017	2.327
LQH_96	0.197	0.048	4.132
Sample	303		
Adjust R^2	0.231		
	FOR NON-CRP FARM		
Constant	0.137	0.027	5.091
OP_RET	-0.048	0.018	-2.637
OP_ED_C	0.013	0.002	6.789
OP_EXP	0.000	0.000	-0.808
RAISE_OP	0.025	0.011	2.197
H_SIZE13	0.034	0.006	5.475
LQH_96	0.189	0.019	9.699
CROPSIZ1	-0.019	0.007	-2.584
CROP17	-0.074	0.010	-7.211
AMTA_A	0.000	0.000	0.958
Sample	1,716		
Adjust R^2	0.117		

Variable definitions are listed in Table 2.4 of Chapter 2.

Due to the differences in the distribution of estimated technical efficiencies, the estimated coefficients of the explanatory variables are different for these two groups, but both of the results are consistent with our economic intuition.[52] In general, farmer and household characteristics explain some difference in technical efficiency. The farmers of younger age, more farming experience and more educated are more efficient, although some of the factors are not statistically significant for the non-participant group. Technical efficiency is higher for the farm operators raised on the farm in the non participant group. This is reasonable finding since it might capture the effect of the human capital (Huffman 2004). For the partial CRP farm group, the higher proportion of land owned by the farm household (as measured by the tenancy variable), the higher is the technical efficiency of the farm. Additionally, the farms receiving more decoupled payments are also more technical efficient. This might be reasonable because the farmer with higher payment from the government might invest in their farms to improve the farming efficiency. Also, the farms with a higher land quality index are more technical efficient. This result is consistent with the finding of Wadud and White (2000).

Concluding Remarks

Focusing on the CRP participation decision of the farm household, we identify those factors affecting both farmers' decisions to participate in the CRP and the level of participation, and its impacts on technical efficiencies and productivities. We propose a three-stage econometric model for the empirical analysis. The first stage estimates a sequential choice model to account for both the CRP participation decision and whether or not the entire farm or only part of it is enrolled in CRP. To our best knowledge, no one has made this particular distinction studying CRP participation. To

[52] We specify slightly different regressors of these two models based on the goodness of fit of each model.

validate the model specification, we test our empirical model to determine if other choices made by the farmer are exogenous, and therefore can be included as explanatory variables. In the second stage, we estimate both a CRP per-acre payment equation and a CRP acreage enrollment equation, correcting for sample selection bias. In the third stage, we estimate differences in technical efficiencies and factor productivities between partial CRP participants and non-participants using the two-stage method of moment estimation. Since whole farm participants are no longer producing agricultural commodities, the comparison are relevant only for partial CRP farms CRP and non-participants. The measures of technical efficiency at the means of the data are compared between groups. The differences in factor productivity between the groups are also compared using the Malmquist TFP formula.

Our empirical findings are encouraging. In terms of model performance, statistical tests confirm the need to control for sample selection. Further, statistical tests support the hypothesis that binary CRP choice and partial CRP enrollment decisions should be considered jointly but specify as two choice structures, since the factors affecting these two decisions are different. This evidence primarily supports our sequential CRP choice model specification. That is, a simple binary choice model that didn’t differentiate between part and whole farm participation would likely have resulted in a model misspecification.

Furthermore, although farmers in areas where soil quality is high are more likely to participate in CRP, the level of participation (as measured by acreage enrolled) is higher in areas where land quality is relatively low. Since the coefficient on the predicted per-acre payment is positive and statistically significant in this acreage equation, the level of participation does increase with the payment level. However, it becomes negative in areas as the proportion of the low land quality increases. The overall price effect on CRP acreage is negative for the whole CRP enrollees. This is perhaps an important distinction to recognize between partial and whole farm participations.

We also find that farmers attempting to protect the future viability of their farming operations by participating in state or local agricultural district programs are located in an agricultural protection zone, etc. are less likely remove cropland from agricultural production by participating in CRP.

Finally, based on estimated production functions and the decomposition to estimate the technical and scale efficiencies, we find that for those who participate in CRP are technical inefficient. However, the difference is offset by the higher scale efficiencies and production frontiers for the CRP participants. Thus, the differences in total factor productivities are small.

CHAPTER FIVE

IDENTIFYING THE RELATIONSHIP BETWEEN CRP PARTICIPATION AND THE OPERATOR'S DECISION TO WORK OFF THE FARM

Introduction

There are three objectives in this chapter. First, we investigate the extent to which the off-farm labor decisions of the farm operator and the CRP participation of the farm household are made independently, are simultaneous, or are determined sequentially. This distinction is a critical link in a larger ongoing research effort to understand those factors that affect participation in environmentally related farm programs. We are particularly interested in how these decisions to work off the farm and participate in the CRP depend on the stock of human capital and risk attitudes of farm operators, as well as the composition of farm household income and wealth. It is also critical to identify how these decisions differ by region and how they are affected by land quality, farm size, and participation in other government programs. Once the appropriate decision making process has been identified, our second objective is investigate how these same factors affect the CRP acreage and hours worked off the farm by the operators. We are also interested in the impact of these two decisions on farm productivity and technical and scale efficiencies.

Because decisions to work off the farm and to participate in CRP are effectively binary choices, the econometric models developed for the empirical analysis are based on a discrete choice framework. To identify the appropriate decision making process, we investigate two alternative families of choice structure. In the first, the farm households' decisions to work off the farm and to participate in the CRP are determined simultaneously. The two major econometric approaches consistent with this simultaneous decision hypothesis are based on a multinomial logit model and a bivariate probit model. These two models differ in the assumptions imposed on the error terms. We determine which specification is preferred on the basis of the likelihood ratio test proposed by Vuong for model selection under a non-nested hypothesis and test the *Irrelevance of Independent Alternatives* (IIA) assumption of multinomial logit model using the Hausman-Wu test.

Second, we examine the possibility that the two choices are made sequentially: the farm household may first make the decision to work off the farm, after which the decision to participate in the CRP is made. Or, the reverse could also be true. Our strategy is to estimate separate models for each possible sequence and test the performance of each. Although a nested multinomial logit model (NLM), based on a generalized extreme value distribution for the error structure, is frequently used to model sequential choices, it is not particularly suitable in this application where the characteristics of the farm households in the sample differ, but the characteristics of the choices available do not. For statistical identification, it would have been necessary to normalize on one of the choices, resulting in a loss of information.

To circumvent this potential difficulty, we take an alternative approach, which, to the best of our knowledge, has not been used to model sequential decisions such as those of interest here. We specify a sequential bivariate probit model that combines the strengths of both a treatment effects model and a bivariate probit model. It is similar to the sequential probit model proposed by Amemiya (1985); and applied by Tunali (1986), but in our case, we have fully observed regimes. In contrast to Amemiya's model, our model also allows for correlation between these two sequential choices. We evaluate the performance of the two estimated models, each representing one of the two possible choice sequences, using a Likelihood Dominance Criterion (LDC); a non-nested test is also utilized to complete the analysis (Pollak and Wales 1991).

Given the appropriate decision making process of the farm household toward CRP participation and the off-farm labor decisions, we are interested in the second stage equations, including CRP payment, CRP acre, off-farm wage and hours worked off the farm. Moreover, we also analyze the economic impact of these two participation decisions in terms of farm productivity, technical and scale efficiencies, and technology.

Econometric Framework

The econometric framework contains three parts. The first part outlines the econometric strategy to determine the decision making process that underlies the off-farm labor supply of farm households and participation in CRP. The empirical specification is motivated in part by the theoretical results in Chapter 3, but to avoid the misspecification of the econometric selection model, we propose several econometric strategies to characterize these decisions. In so doing, we compare the performance of two econometric structures, one that embodies a joint decision process, and the second that embodies a sequential decision process. Throughout, we discuss the model selection criteria by which to determine which choice structure (independent, joint, or sequential) is most appropriate for these two decisions by the farm households. The second part outlines the second-stage response given the appropriate decision making process; while the third part describes the methology for analyzing farm productivity and its decomposition.

Modeling the Joint Choice Structure

When decisions are considered joint, polychotomous choice models are commonly used in empirical analysis. Generally, these models fall into two classes. The first class relies on multiple binary choice rules, defining each decision separately as the binary choice, but allowing for correlation between these binary decisions. If the correlation proves significant, the decisions are truly jointly determined; otherwise they can be regarded more simply as separate binary choices. This forms the basis for testing whether the multiple choices should be regarded as independent or joint. This class of model is often referred to as the multivariate discrete choice model. If a joint normal distribution is assumed between these binary choices, a multivariate probit model is appropriate. Since we are only interested in the two decisions, we focus on the bivariate probit model to consider the joint decisions between CRP participation and off-farm work by the farm operator.

The second class is the multinomial discrete choice model, based on the random utility framework (McFadden (1973; 1974); Dubin and McFadden (1984); Lee (1983)). In this class, the decisions are considered to be joint, without the possibility that each choice could be made separately. If the error term is assumed to have a Type I extreme value distribution, we have the multinomial logit model by McFadden (1974).[53] We utilize the multinomial logit model as the alternative for analyzing the nature of joint decisions between CRP participation and the operator's decision to work off the farm. Regarding model selection, in the case of participation in CRP and/or off-farm work, there are four distinct decisions—each represents one of the four regimes discussed in the section below and depicted at the bottom of Figure 5.1.

[53] Theil (1969) originally studied the choice of transportation mode; Barham *et al*. (2002) studied the adoption of rBST on U.S dairy farms.

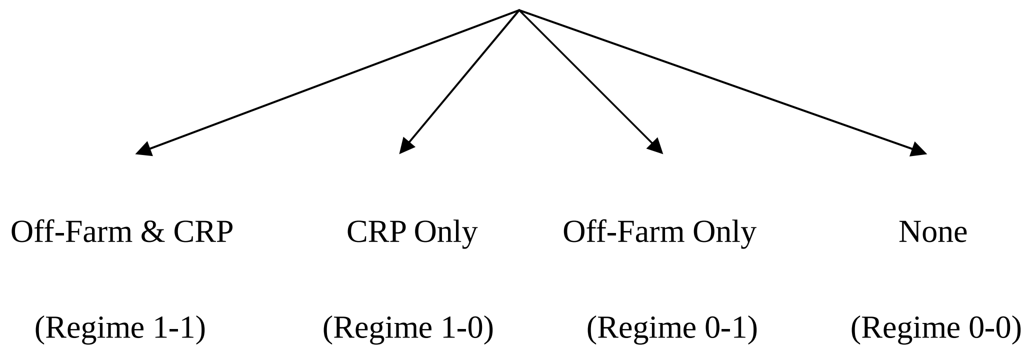

Figure 5.1: Joint Decision Making Structure

<u>Bivariate Probit Choice Model</u>

The econometric framework of the bivariate probit choice model is the extension of the Heckman-Type two-stage method (Heckman 1979). We begin by defining the participation decisions, where each participation decision by the farm household is determined by the net benefit comparison between participation and non-participation. Specifically, the CRP participation decision is determined by the reservation per acre return (perhaps risk adjusted as suggested in the theory from Chapter 3) to the farmer of retaining the land in production with the government's potential payment for land in the conservation reserve program (CRP). The off-farm job decision is determined by comparing the potential off-farm market wage with the shadow value (perhaps also risk adjusted) of the farmer's time in farm production.

The specifications of these two equations are:

(5.1) $P^r = H_{rp} X_{rp} + e_{rp}$ and $P^g = H_{gp} X_{gp} + e_{gp}$

(5.2) $W^r = H_{rw} S_{rw} + u_{rw}$ and $W^g = H_{gw} S_{gw} + u_{gw}$,

where P^r and P^g represent the reservation per acre payment, and the potential government per acre CRP payment; W^r and W^g represent the shadow value of the farming time, and the market off-farm wage. The vectors X_{rp}, X_{gp}, S_{rp}, and S_{gp} are the exogenous variables, and e_{rp}, e_{gp}, u_{rp}, and u_{gp} are the random disturbance terms. The latent binary choice variables (I_1*, I_2*) for the participation decisions of each farmer can be defined as:[54]

(5.3) $I_1* = P^g - P^r = H_{gp1}'X_{gp1} - H_{rp1}'X_{rp1} + (e_{gp} - e_{rp}) = H_1'X_1 + e_1$

$$I_2* = W^g - W^r = H_{gp2}'X_{gp2} - H_{rp2}'X_{rp2} + (u_{gp} - u_{rp}) = H_2'X_2 + e_2 .$$

Suppose the joint distribution of (e_1, e_2) follows a bivariate normal distribution, $N(\begin{bmatrix}0\\0\end{bmatrix}, \begin{bmatrix}1 & \rho\\ \rho & 1\end{bmatrix})$, where the correlation coefficient (ρ) captures the joint nature of these two decisions.

Since it is only the actual decisions, I_i that are observed, the observation rules for these two latent decision variables are:

I_i = 1 (the farmer participates in activity i) iff $I_i* > 0$; and

I_i = 0 (the farmer participates in activity i) iff $I_i* < 0$ i=1,2.

Given the choice structure, there are four potential outcomes, or regimes that can be realized in the data. Since we observe the outcome of each regime, we can define the probability for each regime as (Greene 2002a):

(5.4)

$$P_{11} = \Pr(I_1 = 1, I_2 = 1) = \Pr(e_1 > -H_1'X_1, e_2 > -H_2'X_2) = \int_{-H_1'X_1}^{\infty}\int_{-H_2'X_2}^{\infty}\phi(I_1, I_2, \rho)dI_1 dI_2$$

$$= \Phi(H_1'X_1, H_2'X_2, \rho)$$

[54] For simplicity, subscript 1 refers to the CRP decision, and subscript 2 refers to the off-farm job of the operator.

$$P_{10} = \Pr(I_1 = 1, I_2 = 0) = \Pr(e_1 > -H_1' X_1, e_2 < -H_2' X_2) = \int_{-H_1'X_1}^{\infty} \int_{-\infty}^{-H_2'X_2} \phi(I_1, I_2, \rho) dI_1 dI_2$$

$$= \Phi(H_1' X_1) - P_{11}$$

$$P_{01} = \Pr(I_1 = 0, I_2 = 1) = \Pr(e_1 < -H_1' X_1, e_2 > -H_2' X_2) = \Phi(H_2' X_2) - P_{11}$$

$$P_{00} = 1 - P_{11} - P_{10} - P_{01},$$

where $\phi(I_1, I_2, \rho) = \dfrac{\exp(-1/2 * \dfrac{(I_1^2 + I_2^2 - 2\rho I_1 I_2)}{1-\rho^2})}{2\pi(1-\rho^2)^{1/2}}$, the joint bivariate normal distribution of (I_1,I_2).

The probability of participating in each regime is determined by the observation rule. Since we can observe the four regime participation indexes from the data, the probability of each regime can be specified explicitly. The bivariate probit model is estimated by maximum likelihood methods using the following log likelihood function (Greene 2002a):

(5.5) $$\log L = \sum_{i=1}^{N_1} \log\Phi\{[(2I_1 - 1)(H_1' X_1)], [(2I_2 - 1)(H_2' X_2)], [((2I_1 - 1))(2I_2 - 1)\rho]\}$$

Multinomial Logit Choice Model

The Random Utility Model (RUM) model, proposed by McFadden (1974), has been used widely in applied econometrics; it is consistent with the maximization of utility by the household. Suppose the utility is discrete, and each farmer (*i*) has j alternatives available.[55] The indirect utility of each alternative is:

(5.6) $U_{ij} = V_{ij} + \varepsilon_{ij}$ i= 1..N ; j= 1.. M

[55] In our case, there are four: participate in neither CRP nor off-farm work; participate in CRP only; participate in off-farm work only; or participate in both as depicted in Figure 5.1

Each farmer makes a choice by comparing the utility level from each alternative.

There are two components of the random utility framework. The first, V_{ij}, is the deterministic part of the indirect utility function for alternative *j*, and the second part, ε_{ij}, represents the random nature of the indirect utility. If alternative *s* is chosen, we assume that the indirect utility of alternative *s* provides farmer *i* with the highest utility, when compared to the other alternatives. That is:

$$(5.7) \quad U_{is} = V_{is} + \varepsilon_{is} > V_{ij} + \varepsilon_{ij} = U_{ij} \qquad \forall j \neq s$$

We can re-write equation (5.7) as:

$$(5.8) \quad V_{is} - V_{ij} + \varepsilon_{is} > \varepsilon_{ij}$$

The probability that farmer *i* chooses alternative *s* is:

$$(5.9) \quad \Pr(U_{is} = 1) = \int_{-\infty}^{\infty} \prod_{j \neq s} F(\varepsilon_{ij} < V_{is} - V_{ij} + \varepsilon_{is}) f(\varepsilon_{ij}) d\varepsilon_{ij}$$

$$= \int_{-\infty}^{\infty} \prod_{j \neq s} F(\varepsilon_{ij} < V_{is} - V_{ij} + \varepsilon_{is}) dF(\varepsilon_{ij}) d\varepsilon_{ij}$$

Up to this point, we have imposed no specific distributional assumption on the random errors of the discrete indirect utility functions. In order to derive tractable results, however, specific distributional assumptions are necessary. The most common assumption is the Type I extreme value distribution (McFadden 1974), and this yields the multinomial logit model. Under this multinomial logit model, the probability of farmer *i* choosing the alternative *s* can be further specified as (Maddala 1983):

$$(5.10) \quad \Pr(U_{is} = 1) = \frac{\exp(r_{ij}' w_{ij})}{\sum_{j=1}^{M} \exp(r'_{ij} \, w_{ij})}$$

Given the specification of the probability for each alternative, the structural model can be estimated using the maximum likelihood method. The log likelihood function can be shown as:

$$(5.11) \quad LogL = \sum_{i=1}^{n}\sum_{j=1}^{J} d_{ij} \log \Pr(U_{ij} = 1)$$

where d is the binary indicator for each choice; equal to one if alternative s is chosen.

Modeling the Sequential Decision Choice Structure

Although this joint decision framework above explores the correlation between the CRP and off-farm labor supply decisions, the fundamental assumption is that the two decisions are made simultaneously. In reality, these two decisions may be made sequentially. That is, the farm household might consider one of the decisions first, and makes the other decision sequentially depending on his first choice. Indeed, Lee and Maddala (1994) have noted that if one has no prior information about the decision making process of the decision maker, it is best to model both as a sequential process. Maddala (1983, p. 279) also suggests that it is important to distinguish joint and sequential decisions when applying multiple criteria for determining the appropriate specification. Consequentially, we must examine both orderings of the CRP and off-farm labor choices.

We can again categorize the sequential choice models into two families: multiple and the multivariate choice structures. The nested multinomial logit model fits into the first category, as mentioned in the introduction, however, it is not appropriate for our decision problem because the characteristics of the farm households in the sample differ, but the characteristics of the choices available do not differ. Thus, for statistical identification, it would have been necessary to normalize on one of the choices, resulting in a loss of information. Therefore, as the only other alternative, we adapt a bivariate probit framework to accommodate the sequential decision process. Perhaps, the most straightforward way to analyze the sequential decision making process is to define the nesting structures. These two decisions can be broken down into two levels. Since there is no prior information about the order of these two decisions, we illustrate the sequential decision structure in Figure 5.2 assuming the off-farm work decision is made prior to the CRP participation decision.[56]

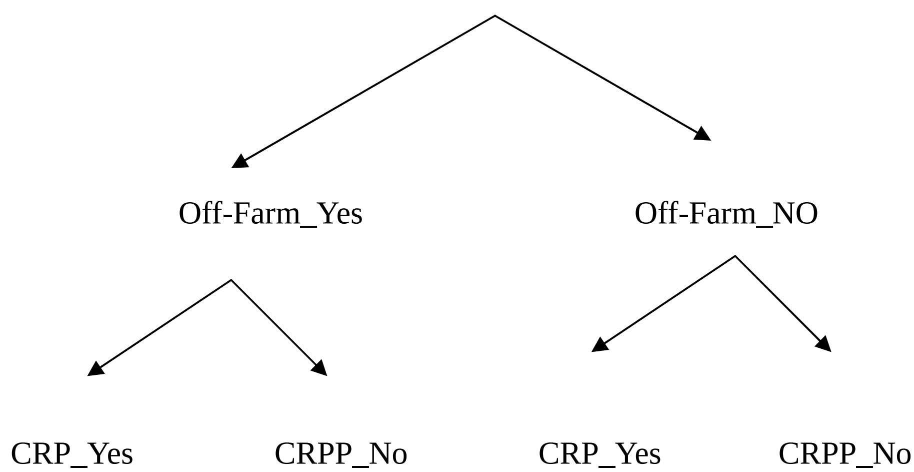

Figure 5.2: Sequential Decision Structure (if off-farm decision is made first)

Nested Multinomial Logit Choice Model

The most straightforward way to model the sequential choice is perhaps the nested multinomial logit model, which relaxes the IIA assumption of the multinomial logit model. Although there are several ways to relax the IIA assumption,[57] the easiest way is to break down the choice set into several multiple-choice levels. In other words,

[56] In the empirical application below, we test the two alternatives (tree structures) based on the model selection criterion.

[57] Alternatively, the multinomial probit model is also mentioned in the literature by assuming the joint distribution of the (ε_{ij}) are multivariate normal. Although this model has some nice features, it is empirically difficult to apply, since this requires the multiple integration of the multivariate normal distribution.

the total choice set is to be grouped into several subgroups instead. In so doing, we allow the variance to differ across the groups while maintaining the IIA assumption within subgroups, which yields a nested multinomial logit model.

Similar to the multinomial logit model, the error term (ε_{ij}) is assumed to be i.i.d. and to follow the generalized extreme value distribution. In order to interpret this model, we follow our definition above and suppose the J alternatives (each represented by a twig on the tree) can be separated into L subgroups (or branches). Accordingly, each individual has to choose to participate first in one of the L branches, and then chooses one of the twigs of the branch.

Given this nested decision structure, the indirect utility function can be specified as:

(5.12) $U_{ij} = V_{ij} + \varepsilon_{ij} = r' w_{ij} + \alpha' q_l + \varepsilon_{ij}$,

where w_{ij} is the vector of the observed attributes varying with both the branch and twig, and q_l is the vector of the observed attributes varying only with the branches. The conditional and unconditional probability that the farmer chooses the alternatives J can be specified as:

(5.13) $\Pr(U_{j/l} = 1) = \dfrac{\exp(r_{ij}' w_{ij})}{\sum_{j=1}^{J} \exp(r_{ij}' w_{ij})}$ (Conditional probability of choosing a twig)

$\Pr(U_l = 1) = \dfrac{\exp(\alpha' q_l + \tau_l IV_l)}{\sum_{l=1}^{L} \exp(\alpha' q_l + \tau_l IV_l)}$ (Probability of the branch choice)

$\Pr(U_j = 1) = \Pr(U_{j/l} = 1) * \Pr(U_l = 1)$ (Unconditional probability)

where the IV_l, the inclusive variable of the branch l, is equal to $\log(\sum_{j=1}^{M} \exp(r_{ij}' w_{ij}))$. The expression ($\tau_l IV_l$) captures the feedback between the twig and the branch of the model, where the feedback structure is consistent with the sequential determination of the choice structure. This expression is also a measure of the correlation among the random error terms and can be used to test the validity of random utility maximization in the nested multinomial logit model (Herriges and Kling, 1996; Borsch-Supan, 1990). Interestingly, the nested multinomial logit model reduces to the multinomial logit model if the parameter τ_l is equal to unity. Thus, testing if the parameter τ_l is equal to unity forms the basis for testing the IIA assumption from the nested logit model against the multinomial logit model. Alternatively, if the inclusive variable (IV_l) is equal to zero, two twigs along the same branch are perfect substitutes. In this case, the choice of twigs within the same branch is independent of the farmer's attributes. From this point of view, the parameter τ_l is a measure of the similarity between the twig choices of the same branch. As long as the probability of each alternative is specified, the structural model can be estimated using full information maximum likelihood estimation. The log-likelihood function we estimated can be shown as:

$$(5.14) \qquad \log L = \sum_{i=1}^{n} \log[\Pr(U_{j/l} = 1) * \Pr(U_l = 1)]$$

Although the nested multinomial logit model is the most straightforward way to analyze the sequential choice structure, it might not be appropriate for the case that the characteristics of the farm households in the sample differ, but the characteristics of the choices available do not differ. For statistical identification purposes, it would have been necessary to normalize on one of the choices, resulting in a loss of information (Falaris 1987). The identification constraint can be illustrated in Figure 5.3. Therefore, as the only other alternative, we adapt a bivariate probit framework to accommodate the sequential decision process.

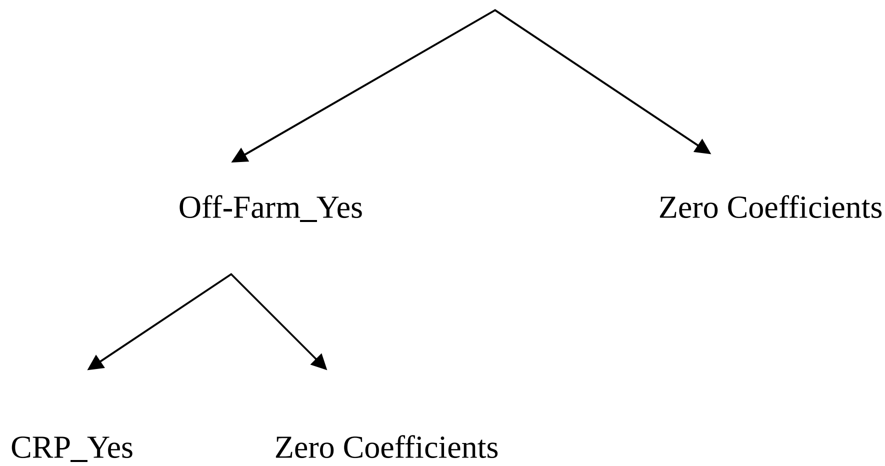

Figure 5.3: Normalization of the Nested Multinomial Logit Model

<u>Sequential Choice Model Based on the Bivariate Probit Framework</u>

Amemiya (1985) was the pioneer in adapting the probit model to sequential choices. He regards the sequential decision process simply as two uncorrelated binary probit choices for ease of computations. Abowd and Farber (1982), Poirier (1980), and Tunali (1986) have proposed similar models that allow for correlation between sequential decisions; their models include Amemiya's original model as a special case.

Because we want to allow for a correlation between a farmer's decision to work off the farm and to participate in CRP, we propose a variation on the model by Tunali (1986). It is a sequential bivariate probit choice model. Since we have no prior information about the choice sequence, we illustrate our model for the case where the farmer makes the off-farm job decision prior to the CRP choice. In this case, the CRP decision, given that the farmer has already chosen to work off the farm, should be regarded differently than the decision to participate in CRP, given that the farmer has decided not to work off the farm. Thus, the unique feature of this formulation is that our model actually involves three choices. Each of them can be specified as a binary probit model, but they are all correlated. The full model structure is:

(5.14) $D_1^* = z_1' r_1 + \varepsilon_1$ $D_1 = 1$ iff $D_1^* > 0$

$D_2^* = z_2' r_2 + \varepsilon_2$ $D_2 = 1$ iff $D_2^* > 0$, conditional on $D_1 > 0$

$D_3^* = z_3' r_3 + \varepsilon_3$ $D_3 = 1$ iff $D_3^* > 0$, conditional on $D_1 < 0$,

where D_1^* is the latent variable for the off-farm labor decision; D_2^* is the latent variable for the CRP decision, given the operator works off the farm; D_3^* is the latent variable for the CRP decision, given the operator does not work off the farm. Following Amemiya (1985) and Tunali (1986), we assume the error terms $(\varepsilon_1, \varepsilon_2, \varepsilon_3)$ follow the trivariate normal distribution: $N[(0,0,0);\begin{bmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{12} & 1 & 0 \\ \rho_{13} & 0 & 1 \end{bmatrix}]$; z contains the parameters of interest for each choice equation, and r is an individual characteristics.[58] Four regimes can be realized from the data:

D_1=1 and D_2=1 when the operator participates in CRP, given the choice not to work off the farm;

D_1=1 and D_2=0 when the operator does not participate in CRP, given the choice not to work off the farm;

D_1=0 and D_3=1 when the operator participates in CRP, given the choice to work off the farm; and

D_1=0 and D_3=0 when the operator does not participate in CRP, given

[58] Our model differs from the one proposed by Tunali (1986) in that we define two different choice structures for the second stage, due to the sequential nature of the choice. More specifically, the correlation between D_2^* and D_3^* is zero, since these two outcomes are mutually exclusive. Our model also differs from the endogenous switching regression model (Lee 1978) since the second-stage equation in our model is the latent dependent variable, instead of the continuous one. This difference requires maximum likelihood estimation.

choice not to work off the farm.

Under the trivariate normality assumption, the probabilities of each regime are:

(5.15) $\Pr(D_1 = 1, D_2 = 1) = \Pr(\varepsilon_1 > -z_1' r_1, \varepsilon_2 > -z_2' r_2) = \Phi(z_1' r_1, z_2' r_2, \rho_{12})$;

$$\Pr(D_1 = 1, D_2 = 0) = \Pr(\varepsilon_1 > -z_1' r_1, \varepsilon_2 < -z_2' r_2) = \Phi(z_1' r_1, -z_2' r_2, -\rho_{12});$$

$$\Pr(D_1 = 0, D_3 = 1) = \Pr(\varepsilon_1 < -z_1' r_1, \varepsilon_3 > -z_3' r_3) = \Phi(-z_1' r_1, z_3' r_3, -\rho_{13});$$

$$\Pr(D_1 = 0, D_3 = 0) = \Pr(\varepsilon_1 < -z_1' r_1, \varepsilon_2 < -z_3' r_3) = \Phi(-z_1' r_1, -z_3' r_3, \rho_{13}).$$

This model can be estimated by the full information maximum likelihoods methods using the following likelihood function:

(5.16)

$$L = \prod_{D_1=1, D_2=1} \Phi(z_1' r_1, z_2' r_2, \rho_{12}). \prod_{D_1=1, D_2=0} \Phi(z_1' r_1, -z_2' r_2, -\rho_{12}). \prod_{D_1=0, D_3=1} \Phi(-z_1' r_1, z_3' r_3, -\rho_{13})$$

$$. \prod_{D_1=0, D_3=0} \Phi(-z_1' r_1, -z_3' r_3, \rho_{13})$$

where $\Phi(.)$ is the cumulative distribution function of the standard bivariate normal random variable.[59]

Testing the Choice Structures and Model Selection Criteria

One primary purpose of this chapter is to identify the choice structure that is the most appropriate for the farmer's decisions to work off the farm and participate in

[59] Since equation (5.16) is highly non-linear, the selection of the initial values might be crucial for estimation. Therefore, the initial values of the parameters for equation (5.16) are determined by estimating a Heckman-Type two-stage model. In the first stage, the standard binary probit choice model for off-farm work is estimated using maximum likelihood methods. Given the consistent estimators of the first stage, the second stage CRP participation is the conditional choice, based on the first stage off-farm decision. Two second-stage models, using the standard Heckman's error correction, provide estimates of CRP participation, conditional on the first-stage decision.

$E(D_2) = z_2' r_2 + E(\varepsilon_2 \mid \varepsilon_1 > -z_1' r_1) = z_2' r_2 + \dfrac{\phi(z_1' r_1)}{\Phi(z_1' r_1)}$ $\quad E(D_3) = z_3' r_3 + E(\varepsilon_3 \mid \varepsilon_1 < -z_1' r_1) = z_3' r_3 - \dfrac{\phi(z_1' r_1)}{1 - \Phi(z_1' r_1)}$.

CRP. To choose between the bivariate probit and multinomial logit decision structures, we use a non-nested test proposed by Vuong (1989) that is based on the likelihood ratio test. To test the nested tree structure for the sequential bivariate probit model, we utilize the "Likelihood Dominance Criterion" (LDC) proposed by Pollak and Wales (1991). The validity of the IIA property in the multinomial logit model is tested using a standard Hausman-Wu (1978) test.

<u>Model Selection Criterion between Two Joint (non-sequential) Decision Models</u>

To choose between the bivariate probit and multinomial logit decision structures, we use a non-nested test proposed by Vuong (1989) that is based on the likelihood ratio test. Given likelihood functions $f(y_i \mid r_i, \alpha)$ and $g(y_i \mid z_i, \theta)$ corresponding to bivariate probit and multinomial logit models, respectively, we estimate of the variance of the difference between the two likelihood functions, defined as:

$$(5.17) \quad w_n^2 = \frac{1}{n}\sum_{i=1}^{n}[\log\frac{f(y_i \mid r_i, \alpha)}{g(y_i \mid z_i, \theta)}]^2 - [\frac{1}{n}\sum_{i=1}^{n}\log\frac{f(y_i \mid r_i, \alpha)}{g(y_i \mid z_i, \theta)}]^2$$

If $E[\log\frac{f(y_i \mid r_i, \alpha)}{g(y_i \mid z_i, \theta)}] = 0$, then there is no basis on which to prefer one model to the other. Under this null hypothesis that there is no difference, Vuong derived the test statistics as: $Z = \frac{LR_n(\alpha, \theta)}{n^{0.5} w_n} \sim N(0,1)$. If this test statistic exceeds the critical value, and $E[\log\frac{f(y_i \mid r_i, \alpha)}{g(y_i \mid z_i, \theta)}] > 0$, then the bivariate probit model is preferred to the multinomial logit model. If this test statistic exceeds the critical value, and $E[\log\frac{f(y_i \mid r_i, \alpha)}{g(y_i \mid z_i, \theta)}] < 0$, then the multinomial logit model is preferred to the bivariate probit model.

Although the multinomial logit model is used commonly by empirical economists in studying individual choices among different alternatives, the model implicitly has the property of the independence of irrelevant alternatives (IIA). Under IIA, the introduction of an alternative will not change the log odds-ratio between the any pair of the existing choices. This assumption is thought to be a weakness of the model; therefore, we test the IIA property of the multinomial logit model using a standard Hausman-Wu test (e.g. Greene (2002a) and Maddala (2001)). If the IIA property is rejected, this model specification might not be appropriate for our choice situation.

<u>Test of the Nested Tree Structure for the Sequential Bivariate Probit Model</u>

To test the nested tree structure for the sequential bivariate probit model, we utilize the "Likelihood Dominance Criterion" (LDC) proposed by Pollak and Wales (1991). After having estimated both models by maximum likelihood, the comparison is based on the log likelihood values and the number of the parameters in each model. (e.g. Kling and Thomson, 1996) With no prior information, we must test the hypothesis:

H_0: CRP participation decision is made prior to the decision to work off the farm.

H_1: Off-farm work decision is made first before the CRP decision.

The model selection criterion under the LDC test is (Pollak and Wales, 1991, p. 236):

(i) LDC prefers H_0 to H_1 if $L_1-L_0< [X(n_1+1)-X(n_0+1)]/2$

(ii) LDC is indecisive if $[X(n_1-n_0+1)-X(1)]/2 > L_1-L_0 > [X(n_1+1)-X(n_0+1)]/2$

(iii) LDC prefers H_1 to H_0 if $L_1-L_0 > [X(n_1-n_0+1)-X(1)]/2$

where L_1, L_0 are the log likelihood values, and n_1, n_0 are the numbers of the parameters in the two models, respectively. X (k) is the chi-square critical value with the degree of freedom of k for a 95% confidence interval.

Second Stage Equations Based on a Bivariate Probit Framework [60]

Given the appropriate bivariate probit choice structure, we are interested in estimating equations for: the CRP per acre payment; acres enrolled; off-farm hourly wage; and hours working off the farm in the second stage equations. Based on this theoretical specification, the reduced forms for these equations can be empirically specified, respectively, as:

(5.18) $P = \alpha_p ' X_p + e_p$

(5.19) $A = \beta_p P + \alpha_a ' X_a + e_a$

(5.20) $W = \alpha_w ' X_w + e_w$

(5.21) $H = \beta_h W + \alpha_h ' X_h + e_h$

where (*P*, *A*, *W*, *H*) represents CRP price, CRP acreage, off-farm wage, and hours worked off the farm, respectively; (X_p, X_a, X_w,X_h) are vectors of the independent variables of the CRP payment and acres equations and the off-farm wage and hours equations, respectively; and $(\alpha_p, \beta_p, \alpha_a, \alpha_w, \beta_h, \alpha_h)$ are the vectors of the parameters to be estimated.

These equations will not appear fully of each regime, depending on the bivariate probit selection rule. Given the corner solutions that arise in either the off-farm participation or the CRP participation decision, the second stage equations of each of the four possible regimes exist as:

Regime 1-1: P>0, A>0, W>0, H>0 (operator works off-farm and participates in CRP);

Regime 1-0: P>0, A>0 (operator does not work off-farm, but does participate in CRP);

Regime 0-1: W>0, H>0 (operator works off-farm, but does not participate in CRP);

---

[60] Given the empirical evidence that the bivariate probit model is more appropriate to capture the joint decision making process (we will discuss it in the empirical section later), we only outline the second stage analysis here. The second stage analysis based on other decision models is shown in Appendix 5.1.

Regime 0-0: none (operator does not work off the farm, and no CRP participation).

In order to apply Heckman's (1979) two-stage approach to deal with possible sample selection bias, we must specify the error structures for each of the four second-stage equation systems. The strategy we propose here is to simply assume each e_j follows a trivariate normal distribution with (e_1, e_2), and the covariance ($\sigma_{j_1}, \sigma_{j_2}$), in order to have tractable and simple estimation. Based on this assumption, Heckman's two stage estimation approach can be easily generated by including two inverse mills ratios--one for the CRP decision and another for the off-farm work decision--into the second-stage equations (Tunali 1986). For regime 1-1, the second-stage equations can be specified as:

(5.22) $$E(P \mid I_1 = 1, I_2 = 1) = \alpha_p' X_p + E(e_p \mid e_1 > -H_1' X_1, e_2 > -H_2' X_2)$$

$$= \alpha_p' X_p + \sigma_{p1} \frac{\phi(H_1' X_1)}{\Phi(H_1' X_1, H_2' X_2, \rho)} \Phi[\frac{H_2' X_2 - \rho H_1' X_1}{\sqrt{1-\rho^2}}]$$
$$+ \sigma_{p2} \frac{\phi(H_2' X_2)}{\Phi(H_1' X_1, H_2' X_2, \rho)} \Phi[\frac{H_1' X_1 - \rho H_2' X_2}{\sqrt{1-\rho^2}}]$$

$$= \alpha_p' X_p + \sigma_{p1}\lambda_1 + \sigma_{p2}\lambda_2$$

$$E(A \mid I_1 = 1, I_2 = 1) = \beta_p \hat{P} + \alpha_a' X_a + E(e_a \mid e_1 > -H_1' X_1, e_2 > -H_2' X_2)$$

$$= \beta_p \hat{P} + \alpha_a' X_a + \sigma_{a1} \frac{\phi(H_1' X_1)}{\Phi(H_1' X_1, H_2' X_2, \rho)} \Phi[\frac{H_2' X_2 - \rho H_1' X_1}{\sqrt{1-\rho^2}}]$$
$$+ \sigma_{a2} \frac{\phi(H_2' X_2)}{\Phi(H_1' X_1, H_2' X_2, \rho)} \Phi[\frac{H_1' X_1 - \rho H_2' X_2}{\sqrt{1-\rho^2}}]$$

$$= \beta_p \hat{P} + \alpha_a' X_a + \sigma_{a1}\lambda_1 + \sigma_{a2}\lambda_2$$

$$E(W \mid I_1 = 1, I_2 = 1) = \alpha_w' X_w + E(e_w \mid e_1 > -H_1' X_1, e_2 > -H_2' X_2)$$

$$= \alpha_w' X_w + \sigma_{w1} \frac{\phi(H_1' X_1)}{\Phi(H_1' X_1, H_2' X_2, \rho)} \Phi[\frac{H_2' X_2 - \rho H_1' X_1}{\sqrt{1-\rho^2}}]$$

$$+ \sigma_{w2} \frac{\phi(H_2' X_2)}{\Phi(H_1' X_1, H_2' X_2, \rho)} \Phi[\frac{H_1' X_1 - \rho H_2' X_2}{\sqrt{1-\rho^2}}]$$

$$= \alpha_w' X_w + \sigma_{w1}\lambda_1 + \sigma_{w2}\lambda_2$$

$$E(H \mid I_1 = 1, I_2 = 1) = \beta_w \hat{W} + \alpha_h' X_h + E(e_h \mid e_1 > -H_1' X_1, e_2 > -H_2' X_2)$$

$$= \beta_w \hat{W} + \alpha_h' X_h + \sigma_{h1} \frac{\phi(H_1' X_1)}{\Phi(H_1' X_1, H_2' X_2, \rho)} \Phi[\frac{H_2' X_2 - \rho H_1' X_1}{\sqrt{1-\rho^2}}]$$

$$+ \sigma_{h2} \frac{\phi(H_2' X_2)}{\Phi(H_1' X_1, H_2' X_2, \rho)} \Phi[\frac{H_1' X_1 - \rho H_2' X_2}{\sqrt{1-\rho^2}}]$$

$$= \beta_w \hat{W} + \alpha_h' X_h + \sigma_{h1}\lambda_1 + \sigma_{h2}\lambda_2$$

A similar approach can be applied to derive the second-stage equations for other regimes. For example, the per acre payment equation and acre enrollment equation for regime (1-0) can be specified as:

(5.23)

$$E(P \mid I_1 = 1, I_2 = 0) = \alpha_p' X_p + E(e_p \mid e_1 > -H_1' X_1, e_2 < -H_2' X_2)$$

$$= \alpha_p' X_p + \sigma_{p1} \frac{\phi(H_1' X_1)}{\Phi(H_1' X_1, -H_2' X_2, -\rho)} \Phi[\frac{-H_2' X_2 + \rho H_1' X_1}{\sqrt{1-\rho^2}}]$$

$$- \sigma_{p2} \frac{\phi(-H_2' X_2)}{\Phi(H_1' X_1, -H_2' X_2, -\rho)} \Phi[\frac{H_1' X_1 - \rho H_2' X_2}{\sqrt{1-\rho^2}}]$$

$$= \alpha_p' X_p + \sigma_{p1}\lambda_1 + \sigma_{p2}\lambda_2$$

$$E(A \mid I_1 = 1, I_2 = 0) = \beta_p \hat{P} + \alpha_a' X_a + E(e_a \mid e_1 > -H_1' X_1, e_2 < -H_2' X_2)$$

$$= \beta_p \hat{P} + \alpha_a' X_a + \sigma_{a1} \frac{\phi(H_1' X_1)}{\Phi(H_1' X_1, -H_2' X_2, \rho)} \Phi[\frac{-H_2' X_2 + \rho H_1' X_1}{\sqrt{1-\rho^2}}]$$

$$- \sigma_{a2} \frac{\phi(-H_2' X_2)}{\Phi(H_1' X_1, -H_2' X_2, \rho)} \Phi[\frac{H_1' X_1 - \rho H_2' X_2}{\sqrt{1-\rho^2}}]$$

$$= \beta_p \hat{P} + \alpha_a ' X_a + \sigma_{a1}\lambda_1 + \sigma_{a2}\lambda_2 .$$

For regime (0-1), only the off-farm wage and hours equations are observed. Using the similar approach above, the off-farm wage and hour equations can be specified as:

(5.24) $$E(W \mid I_1 = 0, I_2 = 1) = \alpha_w ' X_w + E(e_w \mid e_1 < -H_1 ' X_1, e_2 > -H_2 ' X_2)$$

$$= \alpha_w ' X_w - \sigma_{w1} \frac{\phi(-H_1 ' X_1)}{\Phi(-H_1 ' X_1, H_2 ' X_2, -\rho)} \Phi[\frac{H_2 ' X_2 - \rho H_1 ' X_1}{\sqrt{1-\rho^2}}]$$

$$+ \sigma_{w2} \frac{\phi(H_2 ' X_2)}{\Phi(-H_1 ' X_1, H_2 ' X_2, \rho)} \Phi[\frac{-H_1 ' X_1 + \rho H_2 ' X_2}{\sqrt{1-\rho^2}}]$$

$$= \alpha_w ' X_w + \sigma_{w1}\lambda_1 + \sigma_{w2}\lambda_2$$

$$E(H \mid I_1 = 0, I_2 = 1) = \beta_w \hat{W} + \alpha_h ' X_h + E(e_h \mid e_1 < -H_1 ' X_1, e_2 > -H_2 ' X_2)$$

$$= \beta_w \hat{W} + \alpha_h ' X_h - \sigma_{h1} \frac{\phi(-H_1 ' X_1)}{\Phi(-H_1 ' X_1, H_2 ' X_2, -\rho)} \Phi[\frac{H_2 ' X_2 - \rho H_1 ' X_1}{\sqrt{1-\rho^2}}]$$

$$+ \sigma_{h2} \frac{\phi(H_2 ' X_2)}{\Phi(-H_1 ' X_1, H_2 ' X_2, -\rho)} \Phi[\frac{-H_1 ' X_1 + \rho H_2 ' X_2}{\sqrt{1-\rho^2}}]$$

$$= \beta_w \hat{W} + \alpha_h ' X_h + \sigma_{h1}\lambda_1 + \sigma_{h2}\lambda_2$$

More importantly, the inverse mills ratios above for the bivariate probit selection model account for the correlation between these two choice decisions, but in so doing add to the complexity of the calculations. To simplify the calculations, some researchers (e.g. Abdulai and Delgado 1999; Findeis and Lass, 1994) regard the CRP and off-farm work decisions as uncorrelated. Under this assumption, one can easily see that the second-stage equation (use payment equation of regime 1-1 as an example) can be simplified as:

(5.25) $$E(P \mid I_1 = 1, I_2 = 1) = \alpha_p ' X_p + E(e_p \mid e_1 > -H_1 ' X_1, e_2 > -H_2 ' X_2)$$

$$= \alpha_p ' X_p + \sigma_{p1} \frac{\phi(H_1 ' X_1)}{\Phi(H_1 ' X_1)} + \sigma_{p2} \frac{\phi(H_2 ' X_2)}{\Phi(H_2 ' X_2)}$$

Under this simplification, the second-stage equations are expected to be close to the binary choice model, but still contain an inverse mills ratio for each selection decision to correct for the nonrandom sample property.[61]

Technical Efficiency and Farm Productivity

To understand the differences in efficiency between participant groups, we estimate the technical efficiency based on a stochastic production frontier (Aigner *et al.* 1977 and Meeusen and Broeck 1977), along with the bivariate probit choice model. In so doing, we are able to decompose the random shocks to production into two components: those that can be controlled by the farmer and those that are beyond the farmer's control. The stochastic production frontier is estimated in two steps. In the first step, we estimate separate traditional production functions of each group, abstracting from any measure of technical efficiency. We next decompose the error term of the traditional production into a random component and a technical inefficiency component using a generalized method of moment estimation strategy.

[61] The variance-covariance matrix for these second-stage equations must be corrected in order to account for both the endogenous selection and the heteroscedasticity problems. The corrected variance-covariance matrix can be derived following the general procedures proposed by Heckman (1979), but accounting for the jointness in the decision, the computational algebra is more complex. Based on procedures from Greene (2002b), the matrix is:

$$V = (X^*{}' X^*)^{-1} \{ [X^*{}' (\sigma^2 I - \prod) X^* + \theta_1{}^2 X^*{}' G_1 \Sigma G_1 ' X^* + \theta_2{}^2 X^*{}' G_2 \Sigma G_2 ' X^*] \} (X^*{}' X^*)^{-1}$$

where: $X^* = [X, \lambda_1, \lambda_2]$; $\prod = diag\{\pi_1, \pi_2, ... \pi_N\}$;

$$\pi_i = \theta_1^2 (-H_1 ' X_1) \lambda_1 + \theta_2^2 (-H_2 ' X_2) \lambda_2 + (\theta_1 \lambda_1 + \theta_2 \lambda_2)^2$$
$$- [2\theta_1 \theta_2 - \rho(\theta_1^2 + \theta_2^2)] \frac{\phi(-H_1 ' X_1, -H_2 ' X_2, \rho)}{\Phi(-H_1 ' X_1, -H_2 ' X_2, \rho)}$$

Σ is the asymptotic covariance matrix of the bivaruate probit estimation: $G_j = \frac{\partial \lambda_j}{\partial [H_1, H_2, \rho]}$; j =1,2

The first term of {.} is the standard covariance accounting for heteroscedasticity (White, 1980); the second term is used to correct for the endogenous selection problem for the CRP decision, while the third term is used to correct for the off-farm work decision. As such, the asymptotic variance-covariance of the joint decision model should be adjusted for heteroscedasticity and the self-selection bias of both selections.

Finally, we decompose a measure of Total Factor Productivity (TFP) into relative differences in efficiency and technology for each group.

The Production Functions

It is possible to estimate a production function for each group based on the sample selection framework. Production levels are observed for each farmer. Depending on the bivarite probit choice equation for the CRP and off-farm work decisions, the production function of each group can be given as:

(5.26) $Y_j = \beta_j ' X_j + \varepsilon_j$; j=1,2,3,4,

where (Y_j) is the observed production level of each group.

Similar to the second-stage equations above, the conditional expected production of each group, under the trivariate normality assumption for $(e_1, e_2, \varepsilon_j)$, is:

(5.27) $E(Y_j \mid I_1, I_2) = \beta_j ' X_j + E(\varepsilon_j \mid I_1, I_2) = \beta_j ' X_j + \rho_{1j}\lambda_{1j} + \rho_{2j}\lambda_{2j}$

where λ_{1j} and λ_{2j} are inverse mills ratios corresponding to CRP and off-farm work decisions, respectively. With the correction for the bivariate probit selection problem, it can be shown easily that the OLS estimation of equation (5.27) for each group yields consistent estimators for $(\beta_j, \rho_{1j}, \rho_{2j})$.

To calculate technical efficiency, the error term of equation (5.26) is decomposed into its random error and technical inefficiency components, based on the estimators of each production function and an appropriate formulation of the stochastic frontier function specification: Equation (5.26) can be written as:

(5.28) $Y_j = \beta_j ' X_j + \varepsilon_j = Y_j^F + v_j - u_j$

where the variable (Y_j^F) is assumed to be the frontier production functions of each group. Following the standard assumption in the literature on stochastic frontiers (Aigner *et al.* 1977), the random variable (v_j) is assumed to have a normal distribution,

N~(0, σ^2_{vj}); the random variable (u_j) is the technical inefficiency component, and it is assumed to follow a half normal distribution, N^+~(0, σ^2_{uj}). These two components are assumed to be independent.

With this stochastic production frontier, we must first recognize that the expected values of the two one-sided error terms (E (u_j)) do not equal zero. We must rewrite equation (5.28) as:

(5.29) $\hat{Y}_j = \hat{\beta}_j ' X_j + \hat{\varepsilon}_j = Y_j^F - E(u_j) + [v_j - u_j + E(u_j)],$

which implies that:

(5.30) $\hat{\beta}_j ' X_j = Y_j^F - E(u_j)$ and $\hat{\varepsilon}_j = [v_j - u_j + E(u_j)] = e_{scfj} + E(u_j)$

Using the predicted residuals ($\hat{\varepsilon}_j$) from equation (5.26), we can easily see that the parameters (σ_{vj}^2) can be calculated based on the fact that the second and third central moments of ($\hat{\varepsilon}_j$) should be equal to the second and third central moments of (v_j-u_j) since E(u_j) is constant. As such, the parameters ($\hat{\sigma}_{uj}^2, \hat{\sigma}_{vj}^2$) and the composite error can be calculated as:

(5.31) $\hat{\sigma}_{uj}^2 = (\frac{m_3}{\sqrt{2/\pi}(1-4/\pi)})^{2/3}$; $\hat{\sigma}_{vj}^2 = m_2 - (1-\frac{2}{\pi})\hat{\sigma}_{u_i}^2$; $\hat{e}_{scf\ j} = \hat{\varepsilon}_i - \sqrt{\frac{2}{\pi}}\hat{\sigma}_{u\,i}$.

The details of the estimation based on the two-stage-method-of-moments (e.g. Byrnes 1991; Huang *et al*. 2002) are found in Chapter 4. The estimators can be shown to be consistent, although they are not efficient.[62]

Once this stochastic frontier has been estimated, the calculation of the

[62] Alternatively, one could specify the conditional distributions for the components, (v_i-u_i | I_1, I_2), and estimate the stochastic production function along with the choice equation in one step with maximum likelihood method to gain the efficiency. However, this is challenging because the random variable *u* is assumed to be a one-sided error, and the joint distribution is multivariate. To the best of our knowledge, a solution to this particular problem has not been discussed in the literature on stochastic production frontier functions. Consequently, we extend the approach proposed by Huang *et al*. (2002) to construct the two-step strategy of a bivariate choice case. In so doing, we do obtain the consistent estimators from the endogenous switching regression model without the need to specify the distribution for *u*.

technical efficiency index requires point estimates for the random variable *u* of each farmer. Following Jondrow *et al.* (1982), the expected value of *u* given the composite error (*v*-*u*) under the assumption of a half-normal distribution is:

$$(5.32)\qquad E(\hat{u}_{ji} \mid \hat{e}_{scfji}) = \frac{\sigma\lambda}{(1+\lambda^2)}\left[\frac{\phi(\frac{\hat{e}_{scfji}\lambda}{\sigma})}{1-\Phi(\frac{\hat{e}_{scfji}\lambda}{\sigma})} - \frac{\hat{e}_{scfji}\lambda}{\sigma}\right] \quad ;\ j = 1,..,4 \text{ and } i = 1,..,n$$

where $\sigma = (\hat{\sigma}_{uj}^2 + \hat{\sigma}_{vj}^2)^{1/2}$, $\lambda = \dfrac{\hat{\sigma}_{u_j}}{\hat{\sigma}_{vj}}$.

Once these conditional expected values are obtained, the technical efficiency index of each farmer can be calculated as (Kumbhaker and Lovell, 2000):

$$(5.33)\qquad TE = e^{-E(\hat{u}|\hat{e}_{scf\,ji})}.$$

Estimating Productivity and Efficiencies Differences between Groups

One of the main objectives of this study is to examine the farm productivity differences between groups of farmers to understand how CRP participation and off-farm labor supply decision affect productivity or efficiency. We cannot directly compare the technical efficiency indices from the estimation above because the production environment is assumed to differ by group. However, the above results do provide information on differences in technical efficiency for farms within each group. In order to further compare the difference of scale efficiency and productivity, we estimate the Total Factor Productivity (TFP) index proposed by Malmquist (1953) to see the relative productivity differences between groups.[63] Using this approach, we can not only see the differences in TFP, but also identify the sources of the differences

[63] Although the TFP index is usually applied to time series data to measure productivity changes through time, this concept can also be applied to the cross section data. In some resent studies, researchers have applied this approach to make cross-country comparisons in efficiency (Fare *et al*., 1994; Thirtle *et al*., 1995; Fulginiti and Perrin, 1997) and make comparisons for different age groups (Tauer and Lordkipanidze, 2000).

by decomposing TFP into *relative* differences in technical and scale efficiencies and the *relative* differences in technology.

If we consider non-participants as the base group, and use the generalized version of the TFP formula outlined in Coelli (2003) and Lovell (2003), the relative ratio of farm productivity between two groups can be shown as:

$$(5.34) \quad M(y_j, x_j, y_0, x_0) = \frac{TE^{Vj}(y_j, x_j)}{TE^{V0}(y_0, x_0)} * \left[\frac{TE^{V0}(y_0, x_0)}{TE^{Vj}(y_j, x_j)} \frac{TE^{Cj}(y_j, x_j)}{TE^{C0}(y_0, x_0)}\right].$$

$$* \left[\frac{TE^{C0}(y_j, x_j)}{TE^{Cj}(y_j, x_j)} * \frac{TE^{C0}(y_0, x_0)}{TE^{Cj}(y_0, x_0)}\right]^{1/2},$$

where M(.) represents the relative TFP index of group j (except the non participants) relative to group 0 (non-participants). V and C superscripts refer to the variable returns to scale (VRS) and constant returns to scale (CRS), respectively. If $M > 1$, the TFP of group 1 is greater than that for group 0. The term TE^{kj} (y_j, x_j) represents technical efficiency for group j using the level of inputs for group *i*. Total factor productivity is decomposed into three sources. The ratio outside the square brackets measures the relative difference in technical efficiency between groups 1 and 0, which actually measures the relative distance between actual production and the frontier function between groups for the VRS technology. The first term in brackets measures the ratio of scale efficiencies between groups. The second term in brackets measures the relative difference in technology, which is the comparison of the production frontiers between groups. If this term is greater than one, the production frontier of group 1 lies above that for group 0. If this is the case, the production frontier might be higher for farms participating in either both or one of the programs.

Empirical Results

Our empirical results are organized in three sections. The first part provides the estimation results of four choice models (Tables 5.1-Table 5.6). All three models are included for completeness, and so the reader can compare their performances. However, it is only the empirical model for the preferred choice structure that is discussed. Given the estimation of each model, we then access the performance between these models in order to determine the appropriate decision making process of farm households to CRP participation and the decision to work off the farm by the operator. The test results about the joint and the sequential decision structures are summarized in Tables 5.7 and 5.8 based on Vuong's test, Haussman-Wu specification test, and the LDC test. The third part contains a discussion of the second stage results of the appropriate choice structure (Tables 5.10-5.13). The third part discussed the impact of these two program participations in terms of farm productivity (Table 5.14-5.16). The definitions for the variables in each of the estimated equations are reported in Table 2.4 in Chapter 2.

Table 5.1: Bivariate Probit Model Estimation

Variable	Coefficient	Std	b/Std
	Estimation for CRP Equation		
Constant	-4.948	1.414	-3.499
OP_AGE	0.029	0.003	9.405
OP_ED_C	0.073	0.016	4.621
LQH_96	0.544	0.212	2.568
LQL_96	-1.072	0.327	-3.283
EQIP	1.130	0.409	2.762
AGDIST	-1.163	0.266	-4.375
EBI	0.047	0.021	2.184
AMTA_A	-0.030	0.005	-6.331
LDP_A	-0.014	0.003	-5.057
RISK	-0.057	0.018	-3.195
CROP456	-1.921	0.265	-7.236
CROPSIZ1	0.232	0.040	5.732
REGN1	0.164	0.105	1.562
REGN567	-0.386	0.144	-2.679
REGN9	1.247	0.266	4.688
URBAN	-0.014	0.002	-7.905
	Estimation for OP Equation		
Constant	-0.928	0.585	-1.586
OP_AGE	0.139	0.017	8.401
OP_AGESQ	-1.633	0.147	-11.088
OP_ED_C	0.060	0.014	4.269
OP_EXP	-0.018	0.004	-4.983
OP_EXPSQ	0.000	0.000	4.899
H_SIZE	-0.087	0.030	-2.925
CROPSIZ1	-0.597	0.032	-18.682
RAISE_OP	-0.452	0.097	-4.645
MANUF	0.020	0.006	3.614
TRADE	-0.041	0.015	-2.840
AMTA_A	-0.007	0.002	-3.035
LDP_A	-0.003	0.001	-1.908
RISK	-0.017	0.014	-1.185
NETWORT1	-0.003	0.004	-0.879
SP_HMAK	0.250	0.073	3.415
CROP456	-0.878	0.094	-9.356
REGN3	0.287	0.132	2.170
REGN567	-0.214	0.076	-2.795
TENANCY	-0.043	0.023	-1.886
	Correlation Coefficient		
RHO	0.121	0.053	2.292
Sample	2223		
Log-likelihood	-1872		
LR test*	7.126		

** The null hypothesis for LR test is: RHO=0, critical value of x^2 (0.95,1) is 3.84*
Variable definitions are listed in Table 2.4 of Chapter 2.

Table 5.2: Multinomial Logit Model Estimation

Variable	Coefficient	Std	b/Std
	For CRP=1 Only		
Constant	-8.403	4.524	-1.857
OP_AGE	0.060	0.088	0.686
OP_ED_C	0.153	0.041	3.732
LQH_96	1.732	0.606	2.857
LQL_96	-4.447	1.011	-4.400
EQIP	2.105	1.287	1.635
AGDIST	-1.103	0.662	-1.666
EBI	0.079	0.052	1.527
AMTA_A	-0.043	0.012	-3.700
LDP_A	-0.029	0.008	-3.782
RISK	-0.057	0.045	-1.281
CROP456	-3.827	0.865	-4.423
CROPSIZ1	0.225	0.118	1.913
REGN1	-0.142	0.286	-0.498
REGN567	0.044	0.391	0.112
REGN9	1.127	0.678	1.663
URBAN	-0.007	0.006	-1.204
OP_AGESQ	0.132	0.697	0.189
OP_EXP	0.086	0.033	2.578
OP_EXPSQ	-0.001	0.000	-2.972
H_SIZE	-0.047	0.113	-0.420
RAISE_OP	-0.179	0.343	-0.521
MANUF	0.042	0.017	2.449
TRADE	-0.200	0.049	-4.056
NETWORT1	0.015	0.009	1.611
SP_HMAK	-0.204	0.222	-0.920
REGN3	1.121	0.365	3.076
TENANCY	0.024	0.054	0.451

Table 5.2: (Continued)

Variable	Coefficient	Std	b/Std
		For OP=1 Only	
Constant	-10.530	1.872	-5.625
OP_AGE	0.284	0.035	8.035
OP_ED_C	0.113	0.027	4.134
LQH_96	0.481	0.407	1.182
LQL_96	-0.423	0.436	-0.970
EQIP	0.206	1.240	0.166
AGDIST	-0.150	0.299	-0.502
EBI	0.114	0.023	4.954
AMTA_A	-0.006	0.005	-1.067
LDP_A	-0.004	0.003	-1.196
RISK	-0.016	0.028	-0.575
CROP456	-1.546	0.181	-8.556
CROPSIZ1	-1.764	0.201	-8.761
REGN1	-0.360	0.200	-1.803
REGN567	0.317	0.194	1.634
REGN9	-0.348	0.448	-0.778
URBAN	0.006	0.003	1.628
OP_AGESQ	-3.327	0.345	-9.650
OP_EXP	-0.025	0.007	-3.586
OP_EXPSQ	0.000	0.000	3.601
H_SIZE	-0.208	0.052	-4.003
RAISE_OP	-0.615	0.186	-3.300
MANUF	0.053	0.012	4.501
TRADE	-0.063	0.031	-2.012
NETWORT1	-0.029	0.013	-2.162
SP_HMAK	0.461	0.146	3.146
REGN3	0.774	0.330	2.342
TENANCY	-0.099	0.042	-2.322

Table 5.2: (Continued)

Variable	Coefficient	Std	b/Std
	For CRP=OP=1 Only		
Constant	-17.648	6.383	-2.765
OP_AGE	0.247	0.057	4.318
OP_ED_C	0.153	0.039	3.872
LQH_96	0.409	0.577	0.709
LQL_96	-1.161	0.781	-1.486
EQIP	0.226	2.604	0.087
AGDIST	-2.876	1.315	-2.187
EBI	0.255	0.095	2.684
AMTA_A	-0.082	0.014	-5.690
LDP_A	-0.026	0.007	-3.644
RISK	-0.156	0.042	-3.758
CROP456	-6.764	1.957	-3.457
CROPSIZ1	-0.270	0.164	-1.642
REGN1	0.473	0.284	1.661
REGN567	-0.751	0.432	-1.739
REGN9	2.652	0.950	2.791
URBAN	-0.021	0.005	-4.189
OP_AGESQ	-2.504	0.528	-4.746
OP_EXP	-0.016	0.010	-1.573
OP_EXPSQ	0.000	0.000	0.458
H_SIZE	-0.097	0.079	-1.238
RAISE_OP	-1.281	0.256	-4.995
MANUF	0.052	0.016	3.324
TRADE	-0.153	0.042	-3.608
NETWORT1	0.005	0.018	0.259
SP_HMAK	-0.023	0.236	-0.098
REGN3	0.600	0.368	1.632
TENANCY	0.018	0.045	0.416
Sample	2,223		
Loglikelihood	-1,744		
Restrict loglikelihood	-2,701		

Variable definitions are listed in Table 2.4 of Chapter 2.

Table 5.3: Nested Multinomial Logit Model Estimation_OP comes first

Variable	Coefficient	Std	b/Std
	For CRP Equation		
Constant	-12.809	0.438	-29.216
OP_AGE	0.036	0.000	75.740
OP_ED_C	0.102	0.002	46.707
LQH_96	-0.274	0.031	-8.967
LQL_96	-0.795	0.045	-17.505
EQIP	-4.476	1.441	-3.106
AGDIST	-4.516	0.211	-21.357
EBI	0.178	0.007	25.835
AMTA_A	-0.062	0.001	-82.690
LDP_A	-0.016	0.000	-41.547
RISK	-0.197	0.002	-84.651
CROP456	-6.201	0.176	-35.240
CROPSIZ1	0.645	0.012	53.866
REGN1	0.749	0.015	50.385
REGN567	-1.672	0.030	-56.545
REGN9	3.127	0.066	47.423
URBAN	-0.033	0.000	-136.278
	For OP Equation		
Constant	-1.729	0.057	-30.523
OP_AGE	0.255	0.002	156.066
OP_AGESQ	-3.022	0.016	-191.947
OP_ED_C	0.092	0.001	71.370
OP_EXP	-0.028	0.000	-88.086
OP_EXPSQ	0.000	0.000	87.142
HSIZE	-0.138	0.002	-55.869
CROPSIZ1	-1.360	0.008	-163.252
RAISE_OP	-0.851	0.009	-96.613
MANUF	0.033	0.000	67.965
TRADE	-0.052	0.001	-35.562
AMTA_A	-0.007	0.000	-24.764
LDP_A	-0.004	0.000	-23.781
RISK	0.002	0.001	1.659
NETWORT1	-0.001	0.000	-1.643
SP_HMAK	0.489	0.007	68.481
CROP456	-1.508	0.009	-165.466
REGN3	0.504	0.014	36.858
REGN567	-0.205	0.008	-26.371
TENANCY	-0.075	0.002	-47.236
	Inclusive Variable Parameters		
OP_YES	0.498	0.013	38.870
OP_NO	1	--	--
Sample	2223		
Loglikelihood	-751,203		

Variable definitions are listed in Table 2.4 of Chapter 2.

Table 5.4: Nested Multinomial Logit Model Estimation_CRP comes first

Variable	Coefficient	Std	b/Std
	For CRP Equation		
Constant	-6.213	0.187	-33.261
OP_AGE	0.040	0.000	86.794
OP_ED_C	0.118	0.001	78.738
LQH_96	0.849	0.021	39.725
LQL_96	-1.629	0.036	-45.254
EQIP	-1.659	0.060	-27.614
AGDIST	-2.282	0.049	-46.964
EBI	0.062	0.003	22.002
AMTA_A	-0.041	0.001	-74.883
LDP_A	-0.023	0.000	-80.691
RISK	-0.140	0.002	-77.183
CROP456	-2.308	0.090	-25.542
CROPSIZ1	0.237	0.005	45.987
REGN1	0.370	0.010	35.947
REGN567	-0.953	0.017	-56.640
REGN9	2.084	0.030	68.764
URBAN	-0.015	0.000	-87.983
	For OP Equation		
Constant	-7.800	0.249	-31.381
OP_AGE	0.516	0.008	61.635
OP_AGESQ	-5.343	0.074	-72.446
OP_ED_C	0.010	0.003	3.271
OP_EXP	-0.065	0.003	-20.901
OP_EXPSQ	0.001	0.000	21.944
HSIZE	0.007	0.009	0.810
CROPSIZ1	-0.670	0.009	-74.487
RAISE_OP	-0.362	0.023	-15.808
MANUF	-0.007	0.001	-4.908
TRADE	-0.053	0.004	-14.445
AMTA_A	-0.026	0.001	-18.735
LDP_A	0.015	0.001	18.496
RISK	-0.122	0.004	-33.712
NETWORT1	0.015	0.001	10.579
SP_HMAK	-0.377	0.022	-17.294
CROP456	3.939	0.133	29.619
REGN3	-0.821	0.026	-31.786
REGN567	-1.723	0.034	-50.022
TENANCY	-0.030	0.007	-4.281
	Inclusive Variable Parameters		
CRP_YES	-0.143	0.008	-17.837
CRP_NO	1	--	--
Sample	2223		
Loglikelihood	-765,608		

Variable definitions are listed in Table 2.4 of Chapter 2.

Table 5.5: Sequential Bivariate Probit Model Estimation_OP first

	Coefficient	Std	b/Std
	Estimation for OP Decision		
Constant	-1.185	0.605	-1.960
OP_AGE	0.140	0.017	8.180
OP_AGESQ	-1.644	0.153	-10.771
OP_ED_C	0.066	0.015	4.504
OP_EXP	-0.018	0.004	-4.802
OP_EXPSQ	0.000	0.000	4.739
H_SIZE	-0.087	0.030	-2.904
CROPSIZ1	-0.566	0.036	-15.883
RAISE_OP	-0.384	0.102	-3.768
MANUF	0.020	0.006	3.549
TRADE	-0.037	0.015	-2.497
AMTA_A	-0.008	0.003	-2.665
LDP_A	-0.003	0.002	-1.894
RISK	-0.019	0.014	-1.352
NETWORT1	-0.004	0.004	-1.154
SP_HMAK	0.260	0.074	3.521
CROP456	-0.848	0.110	-7.721
REGN3	0.253	0.131	1.937
REGN567	-0.235	0.083	-2.819
TENANCY	-0.041	0.022	-1.837
	Estimation for CRP Decision (given OP=1)		
Constant	-0.473	0.698	-0.678
OP_AGE	0.003	0.001	2.076
OP_ED_C	0.019	0.005	3.678
LQH_96	-0.072	0.066	-1.089
LQL_96	-0.143	0.099	-1.443
EQIP	-0.017	0.239	-0.073
AGDIST	-0.076	0.116	-0.659
EBI	0.010	0.011	0.927
AMTA_A	-0.006	0.001	-5.076
LDP_A	-0.001	0.001	-1.786
RISK	-0.022	0.005	-4.081
CROP456	-0.190	0.080	-2.384
CROPSIZ1	0.084	0.028	2.964
REGN1	0.107	0.032	3.317
REGN567	-0.091	0.050	-1.814
REGN9	0.513	0.118	4.362
URBAN	-0.004	0.001	-6.480

Table 5.5: (Continued)

	Coefficient	Std	b/Std
	Estimation for CRP Decision (given OP=0)		
Constant	0.084	0.353	0.237
OP_AGE	0.006	0.002	3.470
OP_ED_C	0.012	0.005	2.565
LQH_96	0.211	0.066	3.191
LQL_96	-0.340	0.111	-3.072
EQIP	0.271	0.131	2.077
AGDIST	-0.219	0.069	-3.195
EBI	0.000	0.005	-0.025
AMTA_A	-0.004	0.001	-7.607
LDP_A	-0.003	0.001	-5.601
RISK	-0.011	0.005	-2.062
CROP456	-0.118	0.055	-2.135
CROPSIZ1	0.030	0.015	2.042
REGN1	-0.053	0.030	-1.788
REGN567	-0.071	0.040	-1.769
REGN9	0.020	0.071	0.287
URBAN	-0.003	0.001	-4.862
	Coefficient Correlation Estimation		
RHO(0,u)	0.027	0.126	0.626
RHO(1,u)	0.104	0.138	2.082
Sample	2223		
Loglikelihood	-1891		

*** RHO(0,u) is the correlation coefficient between OP and CRP|OP=0*

RHO(1,u) is the correlation coefficient between OP and CRP|OP=1

Variable definitions are listed in Table 2.4 of Chapter 2.

Table 5.6: Sequential Bivariate Probit Model Estimation_CRP first

Variable	Coefficient	Std	b/Std
	Estimation for CRP Decision		
Constant	-4.733	1.547	-3.059
OP_AGE	0.030	0.003	9.141
OP_ED_C	0.074	0.017	4.451
LQH_96	0.471	0.222	2.125
LQL_96	-1.021	0.348	-2.932
EQIP	1.107	0.450	2.458
AGDIST	-1.136	0.279	-4.075
EBI	0.043	0.023	1.846
AMTA_A	-0.030	0.005	-5.765
LDP_A	-0.013	0.003	-4.257
RISK	-0.054	0.019	-2.943
CROP456	-1.977	0.284	-6.974
CROPSIZ1	0.215	0.052	4.096
REGN1	0.193	0.107	1.797
REGN567	-0.406	0.149	-2.733
REGN9	1.223	0.280	4.373
URBAN	-0.015	0.002	-7.859
	Estimation for OP Decision (given CRP=1)		
Constant	0.955	0.620	1.541
OP_AGE	0.041	0.019	2.141
OP_AGESQ	-0.547	0.162	-3.375
OP_ED_C	-0.005	0.008	-0.556
OP_EXP	-0.016	0.007	-2.371
OP_EXPSQ	0.000	0.000	2.561
H_SIZE	-0.008	0.022	-0.356
CROPSIZ1	-0.087	0.023	-3.859
RAISE_OP	-0.161	0.055	-2.924
MANUF	-0.002	0.003	-0.480
TRADE	-0.011	0.008	-1.315
AMTA_A	-0.010	0.003	-2.759
LDP_A	0.000	0.002	0.016
RISK	-0.011	0.009	-1.182
NETWORT1	0.002	0.002	1.189
SP_HMAK	-0.036	0.046	-0.775
CROP456	-0.436	0.279	-1.566
REGN3	-0.148	0.061	-2.406
REGN567	-0.181	0.087	-2.078
TENANCY	0.000	0.009	-0.014

Table 5.6: (Continued)

Variable	Coefficient	Std	b/Std
	Estimation for OP Decision (given CRP=0)		
Constant	0.322	0.175	1.837
OP_AGE	0.034	0.005	6.856
OP_AGESQ	-0.404	0.045	-8.880
OP_ED_C	0.024	0.005	4.977
OP_EXP	-0.005	0.001	-4.163
OP_EXPSQ	0.000	0.000	4.081
H_SIZE	-0.025	0.009	-2.824
CROPSIZ1	-0.223	0.020	-10.920
RAISE_OP	-0.117	0.032	-3.662
MANUF	0.008	0.002	4.153
TRADE	-0.015	0.005	-3.139
AMTA_A	-0.002	0.001	-2.311
LDP_A	-0.001	0.000	-2.936
RISK	-0.001	0.005	-0.230
NETWORT1	0.001	0.000	6.539
SP_HMAK	0.087	0.024	3.645
CROP456	-0.270	0.035	-7.765
REGN3	0.094	0.049	1.902
REGN567	-0.064	0.026	-2.506
TENANCY	-0.016	0.007	-2.196
	Coefficient Correlation Estimation		
RHO(0,u)	0.096	0.131	1.785
RHO(1,u)	-0.019	0.234	-0.224
Sample	2223		
Loglikelihood	-1899		

** *RHO(0,u) is the correlation coefficient between CRP and OP|CRP=0*
RHO(1,u) is the correlation coefficient between CRP and OP|CRP=1
Variable definitions are listed in Table 2.4 of Chapter 2.

Table 5.7: Model Selection Criterion Between Models

	Different in Loglikelihood	Different in Para #	Test Value	Critical Value	**Model Selection**
A. Joint Decision Models					
BVP vs MNL*	--	--	-1.6309	-1.69	**No Preference**
B. Sequential Decision Models					
Sequential BVP**					
OP vs CRP	8.51	3	--	2.83	**OP**
C. Sequential BVP vs Nested*					
OP vs OP	749312	20	--	14.42	**Sequential BVP**
D. Joint vs Sequential Choices					
Sequential BVP vs BVP**	-19	18	--	10.53	**BVP**
E. Jonit vs Independent Choices*					
BVP vs (CRP&OP)			7.126	3.84	**BVP**

*Note: *: Vuong Test; **: LDC Test; ***: LR Test*

OP refers to the case that off-farm decision is made first; CRP refers to the case that CRP decision is made first

Table 5.8:IIA Test of Multinomial Logit Model

Deleted Group	Test Value (x^2)
group 3 only	3.58
group 1 only	2.57
group 0 only	162*
group 2 and 3	9.44
group 1 and 2	18.39
group 1 and 3	2.83
group 2 and 0	92.8*
group 1 and 0	130*

*Critical value is 41.33; * is rejected at 95% level*
grou0: nonparticipants; group1: CRP=1 only
group 2: OP=1 only; group3: CRP=OP=1

Testing the Independent, Joint, and Sequential Decision Structures

We summarize our test results about the joint and the sequential decision structures in Tables 5.7 and 5.8. Based on Vuong's test in part A of Table 5.7, there is no clear preference between the bivariate probit model or the multinomial logit model. Although these results are inconclusive, we do reject the hypothesis of IIA (the independence of irrelevant alternatives) in the multinomial logit model according to the Hausman-Wu tests for four of the nine deleted group combinations involved in the test (Table 5.8).[64] Therefore, on this basis, there is some reason to believe that the bivariate probit model best captures the joint nature of the decisions to participate in CRP and work off the farm.

[64] The Type I extreme distribution assumption of the multinomial logit model implies that the J-log odds ratios between any two pair of alternatives can be computed as: $\log[\frac{\Pr(U_{is}=1)}{\Pr(U_{ij}=1)}] = w_i(r_{is} - r_{ij})$

This shows that the J-log odds ratio for a specific farmer depends only and the coefficients of these two alternatives and these are independent on other alternatives. In other words, the J-log odds ratio is the same of any two alternatives irrespective of the total number of the choices considered. From the behavioral point of view, the IIA constraint might not be very attractive. As such, it might be necessary to test the IIA constraints if multinomial logit model is utilized.

In testing the appropriateness of the sequential bivariate probit model, we must begin with the test for the order in which the two decisions are made. In this case, the results of the LDC test suggest that the decision to work off the farm is made prior to the decision to participate in CRP (Part B, of Table 5.7).[65] In turn, part C of Table 5.7 contains the LDC test that determines the appropriateness of the joint decision structure against the sequential decision structure. Since the LDC test from above suggests that the decision to work off the farm is made prior to the decision to participate in CRP, it is that version of the sequential bivariate probit model that is used in this test. Our result of this test supports the selection of the bivariate probit model. This would reinforce our earlier conclusion that the joint decision model is better able to capture the process associated with decisions to participate in CRP and work off the farm working.

This conclusion is confirmed once again by a test of this joint decision structure hypothesis against a null hypothesis that the two decisions are independent binary choices. This test involves testing the null hypothesis that the correlation coefficient between the decisions in the bivariate probit model is zero. The results of this test are in part D of Table 5.7. Based on the Likelihood Ratio test, we reject the hypothesis that this correlation between these two decisions is zero at the 5% level.

To sum up, there is strong statistical evidence that decisions to participate in CRP and work off the farm are determined jointly, rather than in a sequential fashion or independently.

Estimated Empirical Models

Since the bivariate probit model is the preferred choice, we focus here exclusively the results for that model. The bivariate probit model is a straightforward

[65] LDC had been used as the model selection criterion for testing the sequential structures under the nested multinomial logit model framework (Kling and Thomson 1996; Hauber and Parsons 2000).

extension of the binary choice case, but it allows for a correlation between each binary choice. This special characteristic also provides the basis for justifying the joint rather than an independent decision specification.[66] Table 5.1 presents the maximum likelihood estimation of the bivariate probit model. The parameter (ρ), the correlation between the error terms in the two participation equations does capture the joint nature of these two decisions: ρ is equal to 0.121, and it is statistically different from zero. More formally, the independence assumption between CRP and off-farm work decisions can be tested through a likelihood ratio test (LR) under the null hypothesis that the parameter (ρ) is equal to zero. The LR test value of our model is 7.1, which is greater than the critical value (3.8) at the 5% level.[67]

Determinants of the CRP Participation

Based on the results of bivariate probit model in Table 5.1, participating in CRP depends generally on some characteristics of the farm, the farm operator, land quality, and the circumstances in the local economy. There are also some differences in participation by major ERS production region. The probability of participation in CRP increases with farm size; the probability of participation is lower if the farm is primarily engaged in vegetable or nursery production, rather than cash grain production, which reflects the higher opportunity cost of the vegetable or nursery

[66] Our bivariate probit specification is in contrast to some other current literature studying off-farm job participation that is based a Tobit specification (e.g. Mishra and Goodwin (1997); Goodwin and Mishra (2004); and El-Osta *et al*. (2004)), The one distinct advantage of this bivariate specification is that a separate set of variables can be specified not only to explain participation in CRP and off-farm work, but also to explain CRP payments, CRP acreage enrollment and off-farm wage and hours worked off the farm given participation. Relative to the off-farm work decision in particular Huffman (2004, page 738) argues that: ".. in the Tobit model, the same set of variables determines the probability of off-farm work and hours of off-farm work, given that participation occurs. This, however, is never an appropriate econometric specification because the off-farm wage and reservation wage equations are not identified."

[67] The LR statistics is calculated as: $T^*=-2*(\log L^{R}-\log L^{UR})$, where $\log^{LR}$ is the log-likelihood value of the restricted model, while $\log L^{UR}$ is for the unrestricted model (bivariate probit model). To implement this test, we estimated separate equations for CRP and off-farm work, each specified as a binary probit model. The restricted log-likelihood value is the sum of the values for these two binary probit models.

farms removing land from production.

In addition to the negative effect of the opportunity cost of land on participation, one could also hypothesize that the likelihood of participation would rise with the level of the annual CRP payments. Unfortunately, it is impossible to include such a variable in participation equations such as this, because of the sample selection problem. However, Park and Schorr (1997) argued that the maximum bid price ought to be one of the factors affecting CRP participation. We have no information on actual bids or bids accepted for our sample farms, but we do find that farm households that are located in areas where the EBI scores for land currently enrolled are high are more likely to participate in CRP, *ceteris paribus*. It is likely that in areas where the EBI scores were high, farmers might well expect to have higher bids accepted.

Based on the measures of soil quality related to the general quality of the soil resource in the region described in Chapter 2, participation in CRP rises (falls) as the proportion of land in the surrounding county is classified as high (low) quality. These results suggest that CRP participation may be higher in areas where land is well suited for agriculture and lower in the areas less suitable for crop production.

There are two variables that suggest participation in CRP has something to do with the life-cycle of the farm operator. The likelihood of CRP participation increases with age. Thus, as farmers get older, committing some land to CRP may be one way of reducing operator labor requirements. This may also be a way of holding onto farmland assets until they are needed for the retirement years, or so that they can be passed on through an estate. The fact that there is a positive correlation between the probability of farmers working off the farm and the probability of participation in CRP (as measured by ρ) may also be a way of reducing operator labor requirements. Finally, the probability of CRP participation increases as a farmer’s education level increases; this is perhaps an indication that investments in human capital might lead to increases in CRP. To the extent that these investments also lead to a greater appreciation by farmers of the value of the environmental benefits from CRP, these effects square with the theoretical model in Chapter 3.

In the theory discussed above, there are also several ways in which risk can affect the participation in CRP. As aversion to risk increases, the likelihood of participation in a program where payments are certain, such as CRP, will increase. This conclusion is supported by the negative sign on the variable "RISK" in Table 5.1 (e.g. high values for "RISK" are associated with farmers who prefer more risk). Furthermore, by allowing for decreasing absolute risk aversion (DARA), our theory is also consistent with the fact that decoupled payments, "AMTA_A", reduce the likelihood of CRP participation. With DARA, farmers are likely to be less concerned about diversifying into risk-free income opportunities as wealth increases through decoupled payments.[68] Finally, since commodity program related loan deficiency payments (LDP) reduce farm income variability, these payments also reduce risk averse farmers' concerns for allocating farm resources to program, such as CRP.

Participation in other programs also affects the likelihood for CRP participation. For example, if the farmer is enrolled in a voluntary agricultural district, subject to a farmland preservation easement, is located in an agricultural protection zone or an area zoned exclusively for agricultural use (the variable AGDIST), the farmer is less likely to participate in CRP. Many farmers participate in these types of programs (most of which are state or local programs) out of concern for maintaining their land in agricultural production in rapidly growing areas where there is competition for land for non-agricultural purposes. Therefore, it is hardly surprising that, *ceteris paribus*, these farmers would be less likely to enroll land in a program

[68] By assuming non-constant absolute risk aversion, Hennessey's (1998) framework is also consistent with our results in the sense that he shows that under these conditions, decoupled payments can affect crop production alternatives.

such as CRP that essentially takes land out of production. The fact that the likelihood of CRP participation falls as the proportion of population that is urban rises would seem to reinforce this explanation.[69] In contrast, farmers who participate in EQIP are also more likely to participate in CRP. Participation in both EQIP and CRP could reflect a farmer's stewardship for the environment (reflected in our theoretical section) by removing particularly venerable land from production, while at the same time using more environmentally friendly practices on land still in production.

Determinants of the Off-Farm Work Decision

As expected, the decision of the farm operator to engage in off-farm work also depends on the characteristics of the farm, the farm operator, and the circumstances in the local economy (Table 5.1). As in much of the existing literature (e.g. Sumner 1982; Benjamin and Guyomard 1994; Abdulai and Delgado 1999), our results continue to confirm the fact that older farmers are more likely to work off the farm.[70] However, the effect is nonlinear, with the likelihood of participation increasing with the operator's age up to about age 44, but declining thereafter. Although the operator's education has a positive effect on the probability of participation in off-farm work, the years of experience on the farm has a negative effect that increases at an increasing rate. Farm operators raised on farms are also less likely to work off the farm. Since returns to off-farm labor are likely to less variable than farm returns, the indication that the likelihood of off-farm participation is lower for farm operators willing to accept more risk (a negative coefficient on "RISK" in Table 5.1, a variable that increases as a farmer is willing to accept more risk) is consistent with the theory of risk averse behavior, but the effect is not statistically significant.

The likelihood of working off the farm decreases with family size, but

[69] Duke (2004) also found that the likelihood of participation in CRP is lower in highly urban areas.
[70] Our result is not consistent with the finding in Whittaker and Ahearn (1991), who found that young operators were more likely than older operators to work off the farm.

increases if the spouse is primarily a homemaker. This latter result may not square with the fact that the operator's likelihood of working off the farm increases with the spouse working off the farm. To disentangle these results, we might well have to specify the characteristics of household size in greater detail and deal with the fact that the decision of the spouse to work off the farm may be endogenous. Attempts are made to disentangle these effects in subsequent chapters.

The likelihood of participation in off-farm work declines with farm size and tenancy, and it is lower for vegetable or nursery operations. The negative effects on the likelihood of participation of both net worth and participation in government programs other than CRP may reflect wealth or scale effects on off-farm labor supply (Goodwin and Mishra, 2004). The negative effect of tenancy (as measured by the proportion of acreage owned) on the likelihood for off-farm job participation reflects a greater commitment to agricultural production (*ceteris paribus*) from operators that own their own land. Finally, there is some indication that the strength of the local economy, as measured by the proportion of jobs that are manufacturing, increases the likelihood of participation in off-farm work. The relative extent to which the local economy depends on jobs in the trade sectors reduces the likelihood of participation in off-farm work.

Further Justification of the Bivariate Probit Model

Before leaving our discussion of the bivariate probit choice model, it is important to address the issue of model misspecification. In this section, we focus on testing two primary assumptions imposed on the bivariate probit model. One issue is to investigate whether or not other variables than participation in CRP or off-farm labor supply decision of the operator that are associated with several explanatory variables are exogenous, and therefore can be included as exogenous regressors in the model. The results of related hypotheses tests affect the validity of any policy conclusions involving these variables. Since the bivariate probit model is based on the assumption of a bivariate normal distributed error term, we test this hypothesis as well.

Tests for Other Choices Being Exogenous

As we discussed in Chapter 4, one might argue that some variables specified in both CRP and off-farm labor supply decisions might be endogenous to these two decisions. We test the null hypotheses that these variables are exogenous to the off-farm labor supply decisions by utilizing the methods outlined in Chapter 4.[71] The variables we test are the decision of the spouse to be a home-maker (SP_HMAK); decouple payment received of the farm household (AMTA_A); tenancy of the land ownership (TENANCY). The results presented in Table 5.9 is encouraging, since only the binary variable that whether the spouse is a home maker (SP_HMAK) might be endogenous to the off-farm working decision of the operator. However, it is not statistically significant at the 5% level. The tested results indicate that the null hypotheses for the other two variables are exogenous to the decision of the operator to work off the farm are not rejected.

Table 5.9: Testing for Endogeneity of OP Choice Equation

Variable	T-Value	P-Value
SP_HMAK	-1.74	0.082
AMTA_A	-0.927	0.354
TENANCY	1.099	0.272

Variable definitions are listed in Table 2.4 of Chapter 2.

[71] Since we specify the same variables with CRP choice equation as with CRP model in Chapter 4 and have encouraging results there. We only focus on testing the off-farm labor supply equation here.

Tests for the Bivariate Normality

Since the bivariate probit model relies on the bivariate normality assumption of the error term, it is important to test this assumption as well. To test bivariate normality, we utilize a general non-parametric framework (Horowitz (1993) and Pagan and Ullah (1999)) by comparing the predicted value from the bivariate probit (parametric model) with a non-parametric estimation. If the bivariate probit is specified correctly, the difference between these two predicted values should be only from sampling error. In conducting the test, we compare the predicted probabilities between the bivariate probit model and a non-parametric regression. We discuss the tests in detail in Appendix 5B. To sum up, our result shows that the bivariate probit model is unlikely to suffer from a misspecification problem.

The Second Stage Equations Based on the Bivariate Probit Model

After discussing the factors affecting the joint decisions to participate in the CRP and in off-farm work, we move on to the empirical results for the second-stage equations for CRP per acre payments; acreage enrolled in CRP; off-farm hourly wage; and hours worked off the farm. By correcting for the sample selection problems, we have estimated results for the appropriate subsets of these equations for the three decision regimes associated with the joint decision structure (Figure 5.1).

To correct for the non-random sampling problem in this case, we demonstrated above that two Inverse Mills Ratios (IMR), one corresponding to each participation decision, must be estimated for each of the regimes. They are included in the respective equations. Given this regime structure, each one of the second-stage equations is estimated for two of the three regimes. It makes sense to compare the results across regimes.

CRP Payment Equations

CRP payment equations are estimated for the group of farmers that participates in both CRP and off-farm work (Regime 1-1), and the group of farmers that participates only in CRP (Regime 1-0). Following the standard approach for the wage equation in the labor economics literature, the dependent variable is the logarithm of the per acre CRP payment. Table 5.10 presents the estimated results based on the linear regression. The model fits the data well, since the adjusted R^2 is 0.41 (Regime 1-1) and 0.50 (Regime 1-0). For both groups, the two appropriate Inverse Mills Ratios are statistically significant. The Wald test results for regime 1-1 and regime 1-0 groups under the null hypothesis that both IMR are equal to zero are 8.3 and 7.21, respectively. Both are greater than the critical value of the chi square distribution (x^2 (0.95,2)=5.99).

Table 5.10: Estimated Acreage Payment Equations

Variable	Coefficient	Std	b/Std	Coefficient	Std	b/Std
	Regime 1-1 (CRP=OP=1)			*Regime 1-0 (CRP=1)*		
Constant	1.819	0.022	83.561	3.391	0.472	7.190
OP_EXP	0.020	0.001	38.703	0.039	0.015	2.590
OP_EXPSQ	0.000	0.000	-22.553	-0.001	0.000	-3.242
LQH_96	0.746	0.012	60.692	0.653	0.246	2.660
LQM_96	0.837	0.016	51.497	0.477	0.370	1.290
CROPSIZ1	-0.068	0.006	-12.346	0.010	0.048	0.205
H_SIZE	-0.043	0.002	-26.007	-0.048	0.049	-0.964
REGN1	0.547	0.005	102.023	0.575	0.097	5.956
REGN567	0.025	0.012	2.035	-0.510	0.154	-3.322
CROP17	0.684	0.018	37.650	-0.623	0.209	-2.984
MANUF	0.022	0.000	80.327	0.013	0.006	2.000
IMR_CRP	0.305	0.005	65.434	-0.038	0.100	-0.382
IMR_OP	0.072	0.011	6.248	-0.229	0.143	-1.602
Sample	120			229		
R^2	0.588			0.533		
Adjusted R^2	0.542			0.507		
Wald Test*	8.300			7.210		

** Wald Test: H_0: IMR_CRP=IMR_OP=0; critical value (x^2 (0.95,2)=5.99).*

Variable definitions are listed in Table 2.4 of Chapter 2.

With respect to the factors that determine CRP payments, the results are quite consistent across groups, but the sizes of the effects of certain variables are quite different. To begin, farmers with more farming experience are likely to receive higher CRP payments, but the effect is non-linear. This experience may well contribute to these farmers' effectiveness at bidding and selecting the most appropriate land to enroll and management practice to use on the CRP land.

It is also encouraging that the size of the payment is directly related to the predominance of high and medium quality farmland in the surrounding area. This effect, however, is much larger for the group that participates in both CRP and off-farm labor market. These results are reinforced by the regional dummy variables indicating that per acre payments are higher in the Heartland, but lower in the Eastern Uplands, the Southern Seaboard, and the Fruitful Rim. Unfortunately, we had no farm-specific data that would relate the size of the payment to the quality of the land actually enrolled.

There is one place in which the results for these two groups differ. The payments are higher for cash grain farmers participating in both CRP and off-farm work, but fall for cash grain farmers participating in CRP but not working off the farm. However, the latter is not statistically significant.

<u>Off-Farm Wage Equations</u>

Off-farm wage equations (Table 5.11) are estimated for the group participating in both CRP and an off-farm job (regime 1-1) and for the group participating only in off-farm work (regime 0-1). The dependent variable is the logarithm of the off-farm wage, and the explanatory variables in the models differ somewhat by group. The performance of the equation for regime 1-1 is slightly better than for the other group. The adjusted R^2 is slightly higher (0.271). The Wald test statistics under the null hypothesis that both Inverse Mills Ratios are equal to zero for the two regimes are 9.9 and 5.0, respectively. Both are greater than the 90% level critical value of the chi-square distribution (4.61). These results suggest that the self-selection problems are significant in the wage equation of both groups.

Table 5.11: Estimated Wage Equations

Variable	Coefficient	Std	b/Std	Coefficient	Std	b/Std
	Regime 1-1 (CRP=OP=1)			*Regime 0-1 (OP=1)*		
Constant	1.012	0.023	44.854	1.577	0.016	96.343
OP_ED_C	0.117	0.001	104.118	0.084	0.001	142.973
OP_EXP_F	0.022	0.000	89.127	0.022	0.000	183.673
OP_TECH	0.049	0.008	6.202	0.180	0.003	63.241
OP_JOBR3	-0.058	0.009	-6.199	-0.175	0.005	-36.085
H_SIZE	-0.038	0.002	-20.126	0.040	0.001	44.958
AGRIN	-0.007	0.000	-33.906	-0.021	0.000	-90.783
CROPSIZ1	-0.193	0.005	-42.438	--	--	--
UNEMP	-0.055	0.002	-30.003	--	--	--
TRADE	--	--	--	-0.020	0.001	-28.756
URBAN	--	--	--	0.003	0.000	35.051
MILES	--	--	--	-0.004	0.000	-45.003
IMR_CRP	0.094	0.006	16.169	-0.084	0.005	-15.967
IMR_OP	0.542	0.007	72.259	0.185	0.004	47.671
Sample	120			489		
R^2	0.333			0.266		
Adjust R^2	0.271			0.249		
*Wald Test**	9.910			5.000		

** Wald Test: H_0: IMR_CRP=IMR_OP=0; critical value (x^2(0.95,2)=5.99); critical value (x2(0.90,2)=4.61).*
Variable definitions are listed in Table 2.4 of Chapter 2.

From the estimated equations, the characteristics of the farm operator affect the off-farm wage for both groups. The fact that farm operators with more education are likely to receive higher wages, is consistent with finding in other studies (e.g., Mishra and Goodwin (1997); Abdulai and Delgado (1999)). Three variables related to the nature of the off-farm job also affect the off-farm wage. The off-farm wage is higher, as one would expect, if the off-farm job is a technical job, but it appears that farmers are willing to accept lower wages if their primary motivation for off-farm work is to gain assess to health insurance or other benefits that are not necessarily available to farm households where everyone is working only on the farm. The off-farm wage is also related to the number of years of off-farm work experience.

The conditions in the local economy in the previous year affect the off-farm wage for both groups. The off-farm wage falls with higher proportions of local labor employed in agriculture, although the effect at the margin is more pronounced for those farmers with off-farm jobs but do not participate in CRP. The operators with larger farms who participate in CRP and work off the farm receive lower wages, as do similar farmers in areas where the unemployment rate of the local economy is high. For the operators who work off the farm but do not participate in CRP, the off-farm wage declines with the distance that the farm household is from a town with a population of more than 10,000 or where there is a high percentage of urban residents or where there are large proportions of labor employed in the trade sector of the local economy. These results probably suggest that these off-farm jobs are more likely to be in very rural areas where wages are lower that in more urbanized areas.

CRP Acreage Equations

Farm operators participating in CRP and working off the farm enrolled on average 115 acres in CRP. This is quite a bit lower than the average of 172 acres for those farm operators participating only in CRP. In general these two equations performed well (Table 5.12). The high adjusted R^2 (0.507, 0.502, respectively) are encouraging. In both equations the correction for sample selection are needed.

Table 5.12: Acreage Equation

Variable	Coefficient	Std	b/Std	Coefficient	Std	b/Std
	Regime 1-1 (CRP=OP=1)			*Regime 1-0 (CRP=1)*		
Constant	-792.679	35.664	-22.227	-758.591	35.244	-21.524
OP_AGE	27.020	0.854	31.656	50.338	0.916	54.952
OP_AGESQ	-358.130	8.956	-39.987	-406.254	7.567	-53.689
OP_EXP	-5.209	0.276	-18.906	-33.697	0.469	-71.896
OP_EXPSQ	0.204	0.005	37.730	0.486	0.007	73.557
LQH_96	-549.731	7.441	-73.874	-878.309	7.971	-110.189
LQM_96	-451.874	8.062	-56.047	-669.682	9.024	-74.214
CROP17	249.315	7.114	35.046	10.423	5.296	1.968
EBI	7.016	0.519	13.526	6.448	0.353	18.288
REGN1	-132.069	5.880	-22.461	-159.769	5.745	-27.811
CROPSIZ1	79.465	3.028	26.239	101.963	1.446	70.492
H_SIZE	6.252	0.750	8.339	11.874	1.308	9.081
AMTA_A	-11.607	0.373	-31.106	-5.270	0.134	-39.335
MANUF	-7.035	0.282	-24.937	-0.499	0.207	-2.416
UNEMP	38.220	0.587	65.155	-2.426	0.501	-4.845
OP_EXP_F	-3.719	0.116	-32.011	--	--	--
PLQL	-2.674	0.242	-11.050	-11.883	0.216	-55.058
P_HAT	4.263	0.208	20.456	5.176	0.148	34.910
W_HAT	2.827	0.204	13.882	--	--	--
WAMTA	0.818	0.030	26.901	--	--	--
IMR_CRP	-90.579	2.728	-33.206	-38.257	2.914	-13.127
IMR_OP	106.070	6.134	17.291	138.094	4.430	31.170
Own price elas**	1.309			1.562		
Cross price elas**	0.716			--		
Sample	120			229		
R^2	0.507			0.502		
Adjust R^2	0.407			0.460		
*Wald Test**	6.540			8.270		

** Wald Test: H_0: IMR_CRP=IMR_OP=0; critical value (x^2 (0.95,2)=5.99)*

***Own price elasticity and cross price elasticity are calculated based on sample mean.*
Variable definitions are listed in Table 2.4 of Chapter 2.

The explanatory variables of these CRP acreage equations relate to operator's characteristics, farm and family structure, environmental quality, and the local economy conditions. In order to capture the interaction between these two decisions, the off-farm wage and off-farm work experience are included in the CRP acreage equation for those who participate in both programs.

To begin, we focus on the CRP acreage in response to changes in CRP payments and off-farm wages.[72] Consistent with the result from the binary CRP choice model (Chapter 4), the estimated CRP payments are positive and significant explanatory variables of both acreage equations.[73] Thus, there are upward sloping CRP acreage supply functions in both cases. Since the own price elasticities for these two groups based on the sample mean of each group are 1.309, 1.562, respectively, farmers who participate in both programs are slightly less payment responsive. Because of the interaction between per-acre payment and low land quality (PLQL), the acreage response to payment falls and can become negative in areas where there is a high proportion of low quality land. We depict the marginal CRP acreage response to low land quality for both groups in Figures 5.4-5.5, respectively. For the group that participates only in CRP, the CRP acre response to payment is negative in areas where about 45% of the land is low quality. These results seem consistent with the belief by some that payments have been raised to attract high quality land in some areas, but are also consistent with farmers' submitting lower bids to ensure that bids for low quality land are accepted.

[72] Following the common practice in studies of labor markets (e.g., Wales and Woodland, 1980; Killingsworth. 1983; and Fernandez *et al.* (2001), we use the predicted per acre payment and per hour off-farm wage as the instruments for payment and wage variables of the acreage equations.
[73] This is consistent with Suter (2004), who found that annual incentive payments affect CREP enrollment in buffer strips, but this effect was apparent only after he used a refined estimate of eligible farmland derived from GIS data on the amount of agricultural land along streams in the target watersheds. However, it is inconsistent with much of the previous literature, particularly studies based on county-level analysis, where the acres enrolled fall as payments rise (e.g. Fleming, 2004 and Goodwin *et al*., 2004).

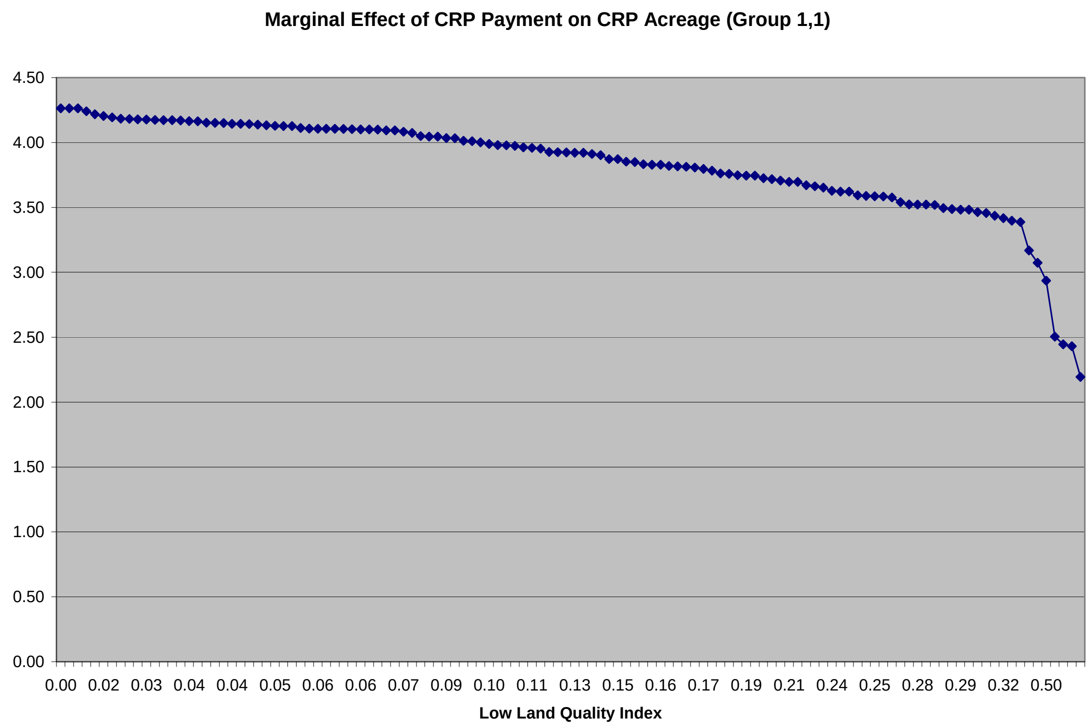

Figure 5.4: Marginal Effect of CRP Price on CRP Acreage in Group (1, 1)

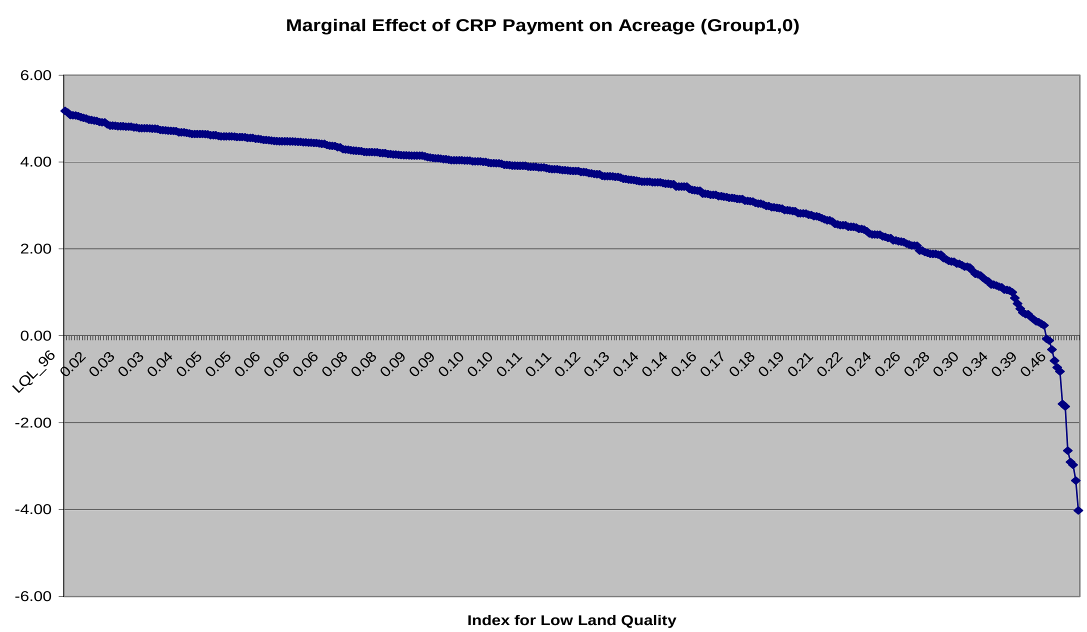

Figure 5.5: Marginal Effect of CRP Price on CRP Acreage in Group (1,0)

There is an inelastic, but positive, estimated cross price elasticity of CRP acreage with respect to the off-farm wage (0.716) for farmers participating in both programs. Thus, operators receiving higher wages appear to have an incentive to work less on the farm, but in so doing, they take additional land out of production and commit it to CRP. We found that the marginal effect of the off-farm wage on CRP acres also depends on decoupled payments (AMTA_A), and the effect increases dramatically if the farm household receives more decoupled payments (Figure 5.6).

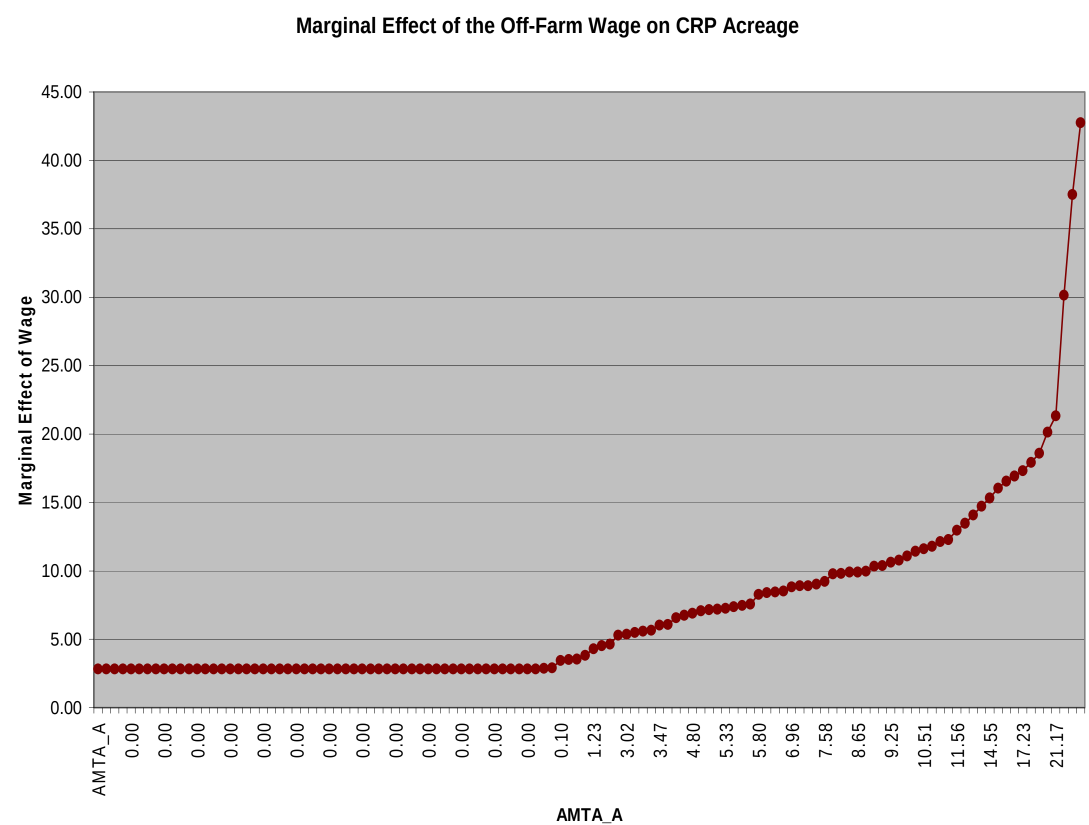

Figure 5.6: Marginal Effect of Off-Farm Wage on CRP Acreage in Group (1,1)

Other factors included in these equations affect CRP acreage in much the same way for each group, but the magnitudes of the effects differ by group. Older farmers enroll more acres in CRP, although the effect is non-linear. CRP acreage also increases with both farm and family size, and for cash grain farms, but acreage decreases with the operator's experience in farming, perhaps reflecting in part a higher opportunity cost of farm labor for more experienced operators.

It is evident from Table 5.12 that CRP acreage is lower in areas where there is a high proportion of high quality land. This is somewhat at odds with the results from the CRP participation equation, where the likelihood of participation in CRP is increased as the proportion of land that is of high quality in a locality increases. This could be symptomatic of a problem in adverse selection. Given the decision to participate in CRP, farmers are less likely to enroll high or medium quality land into CRP; rather they keep it in crop production. This result would also seem to be reinforced by the fact that CRP participants in the Heartland tend to enroll less land in the program. It is difficult to know if these findings are consistent with one of the primary goals of CRP, the reduction of soil erosion and other environmental residuals associated with agricultural production. There is consistency only if it is the poorer quality land that is more subject to erosion and more environmentally venerable. In terms of the goals of CRP, it is encouraging that for regions with higher EBI scores, there is a tendency for CRP acreage to be higher as well.

In terms of other farm programs, CRP acreage falls as decoupled payments rise. This reinforces the negative effect of decoupled payments on the probability of CRP participation. However, the marginal effect of decoupled payments on CRP acres depends on the off-farm wage, the indirect effect through the interaction term (WAMTA) of group (1,1). If the farm operator earns high off-farm wage rate, the marginal effect of decoupled payments on CRP acres could be positive (Figure 5.7).

Hours Worked Off the Farm

To complete our understanding of farm operators' joint decisions to participate in CRP and to work off the farm, we estimate equations for the hours worked off the farm by operators who have chosen to do so (Tables 5.13). These equations did not perform as well as the other second-stage equations, particularly in terms of the adjusted R^2. For both groups of farmers who have off-farm jobs, the joint tests of the two Inverse Mills Ratios are significant at least at the 10% level, suggesting that we have corrected for any sample selection problems.

For both groups, the own-wage elasticities of hours worked off the farm are positive, 0.366 and 0.004 respectively. Although these small elasticities may seem surprising, they are consistent with earlier results by Huffman and Lange (1989).[74] One explanation may be the fact that many off-farm jobs have prescribed work schedules. In contract to earlier literature, we found that the marginal effect of the off-farm wage on off-farm hours also depends on the decoupled payments received by the farm household. The indirect effect comes through the interaction term between the off-farm wage and the decoupled payments (WAMTA). However, both direct and indirect effects positively contribute to the off-farm labor supply (Figure 5.8).

[74] Huffman and Lange (1989) analyze the off-farm labor supply for Iowa family farmers. The own price elasticity for the husband was 0.091.

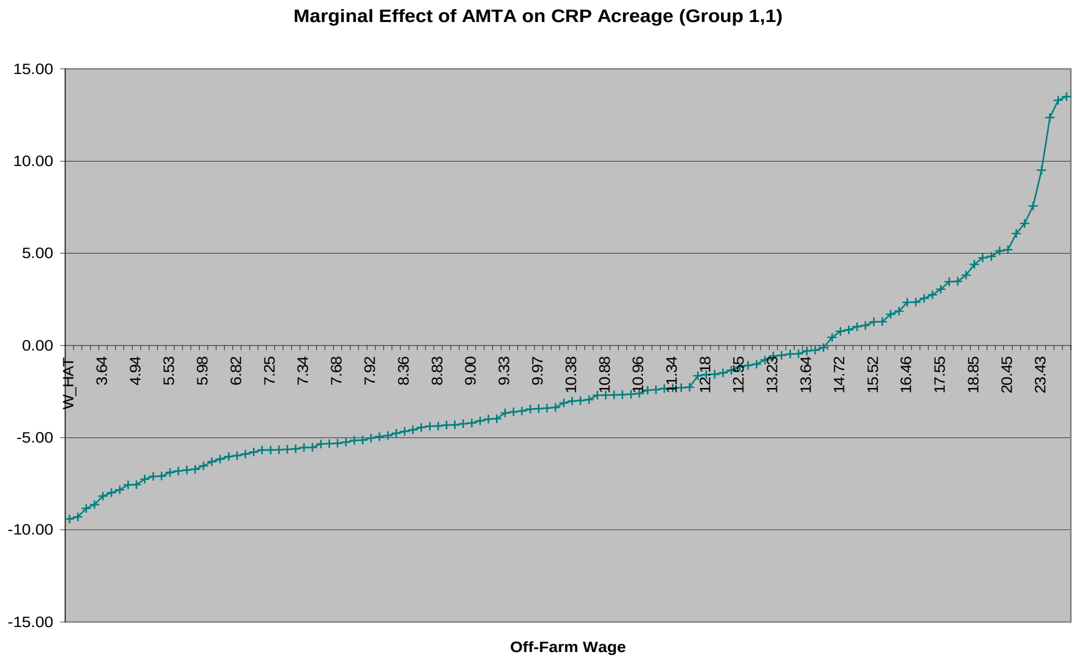

Figure 5.7: Marginal Effects of decoupled payments on CRP Acres in Group (1,1)

For those farmers both working off the farm and participating in CRP, there is a positive cross-price elasticity of hours worked off the farm with respect to CRP payments (0.273), and it is slightly smaller than the own price effect. This result is consistent with the complementary cross-price effect in the CRP acreage equation. In this case, a logical interpretation of the result is: as CRP payments increase, the increase in CRP acreage reduces the demand for labor on the farm, thus making it available for off-farm purposes.

Table 5.13: Equations for Hours Worked Off the Farm

Variable	Coefficient	Std	b/Std	Coefficient	Std	b/Std
	Regime 1-1 (CRP=OP=1)			*Regime 0-1 (OP=1)*		
Constant	369.749	77.056	4.798	3136.368	29.958	104.691
OP_AGE	141.364	3.205	44.104	-6.772	1.187	-5.704
OP_AGESQ	-1637.399	33.934	-48.252	56.595	13.940	4.060
OP_EXP_F	-17.033	0.441	-38.616	--	--	--
RAISE_OP	-491.684	8.403	-58.514	--	--	--
CROPSIZ1	-169.848	11.611	-14.629	-232.665	6.092	-38.191
H_SIZE	--	--	--	-44.848	1.206	-37.186
TENANCY	-53.188	2.562	-20.763	--	--	--
AMTA_A	-123.664	1.442	-85.729	-4.377	0.136	-32.274
LDP_A	-10.489	0.258	-40.669	-4.059	0.084	-48.090
RISK	-50.413	1.433	-35.170	-13.816	0.659	-20.965
TRADE	-68.783	1.356	-50.741	-19.044	0.816	-23.329
MANUF	2.689	0.558	4.823	13.319	0.283	47.006
UNEMP	9.899	2.337	4.236	--	--	--
REGN3	-26.434	10.175	-2.598	-1023.491	6.740	-151.864
SERV	--	--	--	-4.986	0.368	-13.550
DIST_OP	--	--	--	-0.357	0.009	-38.477
MILES	--	--	--	8.584	0.091	94.312
CROP17	--	--	--	-38.253	4.110	-9.308
REGN567	--	--	--	-296.027	3.598	-82.270
REGN9	--	--	--	191.597	11.107	17.249
SP_HMAK	--	--	--	17.937	3.501	5.124
OP_RET	--	--	--	-694.788	13.032	-53.315
NETWORT1	--	--	--	-3.586	0.299	-11.982
URBAN	--	--	--	0.803	0.102	7.883
W_HAT	7.522	0.824	9.127	0.528	0.235	2.247
P_HAT	11.820	0.249	47.555	--	--	--
WAMTA	8.777	0.115	76.543	--	--	--
IMR_CRP	143.477	10.438	13.745	614.979	8.654	71.066
IMR_OP	491.551	24.744	19.865	-384.610	9.513	-40.431
Own price elas**	0.366			0.004		
Cross price elas**	0.273			--		
Sample	120			489		
R^2	0.451			0.502		
Adjust R^2	0.353			0.460		
*Wald Test**	5.867			8.760		

* *Wald Test:* H_0 *: IMR_CRP=IMR_OP=0; critical value (*x^2 *(0.95,2)=5.99); critical value (x2(0.90,2)=4.61)*

***Own and cross price elasticity and cross price elasticity are calculated based on sample mean.*

Variable definitions are listed in Table 2.4 of Chapter 2.

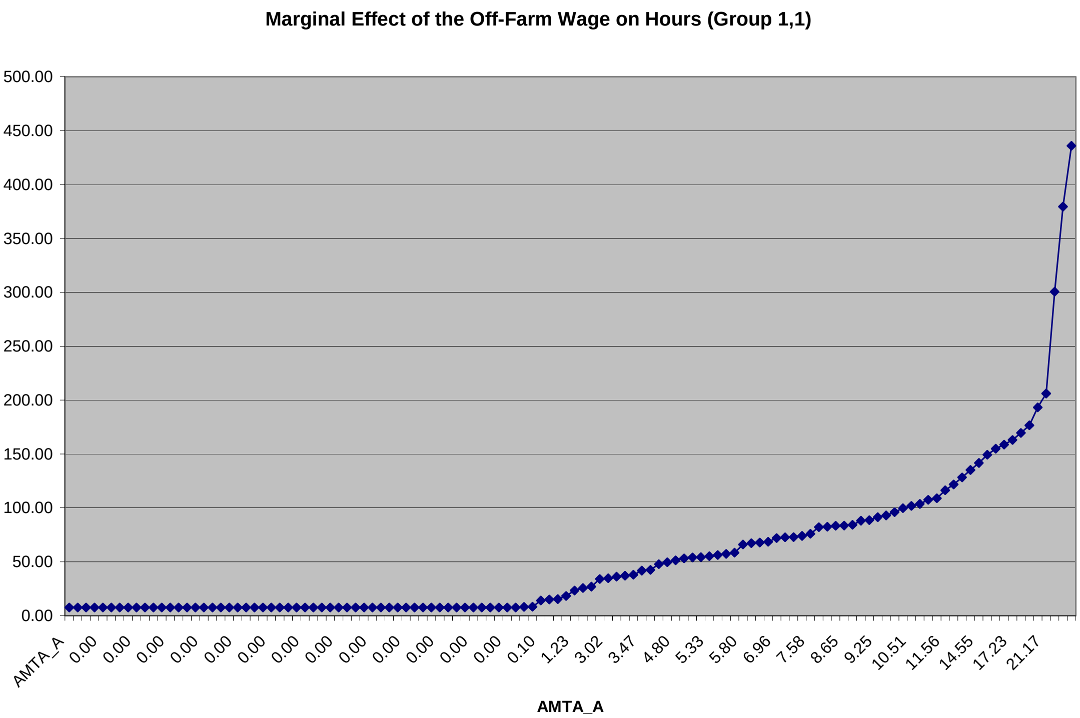

Figure 5.8: Marginal Effect of Off-Farm Wage on Off-Farm Hours in Group (1,1)

For both groups, the commitment of time to off-farm work is higher for the more risk averse farm operators. In contrast, both decoupled payments and loan deficiency payments reduce the downside risk to income from farm production. All else equal, farmers with off-farm jobs receiving these payments tend to work fewer hours off the farm; the magnitudes of these effects differ between the groups. However, we also found that the marginal effect of decoupled payments on off-farm labor supply depends on the off-farm wage rate, which can be regarded as the indirect effect along with the direct effect through (AMTA_A) for group (1,1). The off-farm labor supply can increase if the farm receives a relative high off-farm wage (Figure 5.9).

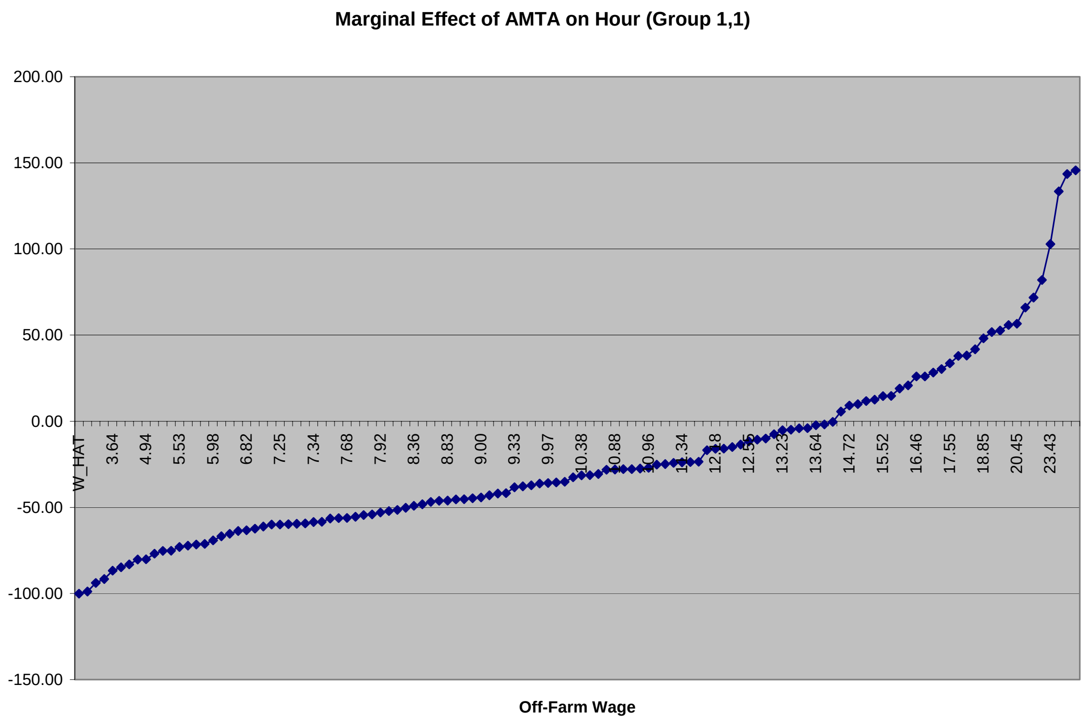

Figure 5.9: Marginal Effect of Decoupled Payments on Off-Farm Hours in Group (1,1)

The effects of operator age on hours worked off the farm differ for the two groups. Older farmers working off the farm and participating in CRP tend to work more hours off the farm than younger farmers in the same group. Older farmers participating in off-farm labor market, but not in CRP, tend to work fewer hours off the farm. This latter result is consistent with that by Goodwin and Mishra (2004).

Those farm operators with off-farm jobs and land in CRP tend to work fewer hours off the farm if they were raised on a farm. Those farmers with more farm experience and who own much of their farmland also tend to work fewer hours in their off farm jobs. These results are consistent with the hypothesis that these types of farmers are likely to be more heavily invested in farm-specific human capital, thus increasing the relative shadow price of farming.

The group of farm operators participating only in off farm work commit fewer hours to that job as farm household net worth increases. In contrast, farmers in this group tend to work longer hours if their spouse is primarily a homemaker. Finally, as one would expect, farm operators in this group that have an off farm job, but who classify themselves as retired, work fewer hours off the farm than others in the group.

Estimating the Technical and Scale Efficiencies and Productivity

As introduced above, we next identify the effect of CRP participation by first estimating four separate production functions, one for CRP participants and one for non-participants. The second step is to estimate the technical efficiency of each farm household by decomposing the compound error on the frontier function into technical efficiency and random shock components. Finally, we compare the different performance regarding the technical and scale efficiencies, production frontier, and total factor productivity of four groups.

<u>The Production Function</u>

To investigate differences in farm productivity, we specify the translog production functions for each group under the variable return to scale technology.[75] All of the output and input variables are specified in logarithm. Gross cash sales are used as the measure of production, while there are four inputs, hours worked on the farm (LGHOUR), operated cropland (LGLAND), hired labor cost (LGLABOR), and capital (LGCA). The hired cost includes regular hired labor and contract labor; Capital is measured by the fixed value of building and farm equipment, excluding the dwelling. Table 5.14 contains estimates for four translog production functions, one for the group of CRP participants, one for the group working off the farm, one for the group doing

[75] We specify the production function as a translog instead of the Cobb-Douglas because its flexibility. We test the translog production function against the Cobb-Douglas. Our LR test suggests utilizing the translog production function is appropriate.

both, and one for the group doing neither. These production functions are estimated within an endogenous switching regression framework. This identifies inherent differences in farm production by group. For three of the four groups, the Wald tests for the joint significance of the two Inverse Mills Ratios are statistically significant. In general, the translog production functions fit the data well. The estimated production elasticities, calculated based on the sample means, of the inputs based on the sample mean are all positive, but they are different across groups. For example, the economies of scale range from a high of 1.462 for the group participating in neither CRP nor off-farm work, to a low of 0.85 for the group participating in CRP only.

Table 5.14: Translog Production Function by Groups

Variable	Coefficient	Std	t-value	Coefficient	Std	t-value
	For CRP=OP=1			**For OP = 1 ONLY**		
Constant	-17.424	6.176	-2.821	-1.038	0.665	-1.561
LGHOUR	1.232	2.126	0.579	0.114	0.188	0.607
LGLAND	-0.117	1.009	-0.116	-0.215	0.238	-0.900
LGLABOR	0.986	0.462	2.133	0.031	0.077	0.407
LGCA	2.831	1.702	1.663	-0.216	0.195	-1.109
HOURSQ	-0.107	0.162	-0.663	0.006	0.016	0.396
LANDSQ	-0.087	0.104	-0.840	0.107	0.020	5.346
LABORSQ	0.014	0.013	1.051	0.053	0.005	11.221
CASQ	0.198	0.127	1.559	0.036	0.015	2.382
HOURLAND	0.522	0.212	2.462	0.027	0.032	0.822
HOURLABR	-0.160	0.048	-3.330	-0.031	0.013	-2.317
HOURCA	-0.278	0.233	-1.192	0.033	0.027	1.241
LANDLABR	0.053	0.035	1.492	-0.039	0.011	-3.427
LANDCA	-0.402	0.130	-3.091	-0.052	0.028	-1.842
LABORCA	-0.036	0.057	-0.631	-0.001	0.012	-0.102
IMR_CRP	0.513	0.226	2.271	-0.031	0.185	-0.168
IMR_OP	0.510	0.256	1.994	-0.136	0.164	-0.825
Elasticity						
Hour	0.168	0.013	12.856	0.341	0.068	5.032
Land	0.460	0.156	2.950	0.553	0.057	9.710
Labor	0.091	0.075	1.210	0.259	0.023	11.024
Capital	0.296	0.152	1.951	0.154	0.063	2.442
Reture to Scale	1.101			1.306		
R^2	0.684			0.707		
Adjusted R^2	0.627			0.699		
Wald Test	7.42			1.36		

Table 5.14: (Continued)

Variable	Coefficient	Std	t-value	Coefficient	Std	t-value
	For CRP=1 ONLY			**For CRP = OP = 0**		
Constant	-20.003	6.134	-3.261	-4.299	1.975	-2.177
LGHOUR	1.847	1.791	1.031	-0.865	0.330	-2.619
LGLAND	1.608	1.323	1.216	0.475	0.335	1.421
LGLABOR	0.492	0.280	1.754	0.615	0.094	6.566
LGCA	1.768	1.243	1.422	0.569	0.509	1.118
HOURSQ	-0.128	0.185	-0.690	0.137	0.024	5.656
LANDSQ	-0.277	0.098	-2.810	0.054	0.011	4.800
LABORSQ	0.011	0.008	1.414	0.040	0.003	14.484
CASQ	-0.080	0.119	-0.673	0.095	0.033	2.828
HOURLAND	0.289	0.224	1.291	-0.011	0.046	-0.236
HOURLABR	-0.049	0.056	-0.886	-0.031	0.014	-2.292
HOURCA	-0.178	0.188	-0.950	-0.073	0.073	-0.995
LANDLABR	-0.052	0.037	-1.382	-0.044	0.008	-5.197
LANDCA	0.106	0.163	0.650	-0.053	0.025	-2.111
LABORCA	0.038	0.036	1.061	-0.067	0.011	-6.153
IMR_CRP	0.251	0.150	1.678	0.145	0.123	1.182
IMR_OP	0.376	0.168	2.239	-0.463	0.083	-5.594
Elasticity						
Hour_els	0.305	0.424	0.721	0.463	0.104	4.468
Land_els	0.019	0.216	0.089	0.307	0.042	7.244
Labor_els	0.179	0.076	2.340	0.382	0.024	16.147
Capital_els	0.347	0.153	2.271	0.310	0.056	5.538
RTS	0.850			1.462		
R^2	0.861			0.824		
Adjusted R^2	0.849			0.821		
Wald Test	7.94			43.12		

Wald Test: H_0*:IMR_CRP=IMR_OP=0; critical value (*x^2 *(0.95,2)=5.99)*

Table 5.15: Comparisons of Technical Efficiency and Productivity

Technical Efficiency for Each Group	
T.E (CRP=OP=1)	0.536
T.E (CRP=1)	0.421
T.E (OP=1)	0.474
T.E (None)	0.428
Ratios of Technical Efficiencies	
T.E Ratio (CRP=OP=1 vs none)	1.253
T.E Ratio (CRP=1 vs none)	0.984
T.E Ratio (OP=1 vs none)	1.106
Ratios of Economic Scale Efficiencies	
T.E Ratio (CRP=OP=1 vs none)	0.995
T.E Ratio (CRP=1 vs none)	1.126
T.E Ratio (OP=1 vs none)	1.013
Ratios of Production Frontiers	
P.F Ratio (CRP=OP=1 vs none)	0.670
P.F Ratio (CRP=1 vs none)	0.838
P.F Ratio (OP=1 vs none)	0.889
Ratios of Total Factor Productivities	
T.F.P Ratio (CRP=OP=1 vs none)	0.834
T.F.P Ratio (CRP=1 vs none)	0.928
T.F.P Ratio (OP=1 vs none)	0.996

** Note: ratio is calculated based on non-participant group.*

Productivity and Efficiency Comparisons

We utilize the Malmquist TFP Index formula to estimate differences between groups, in terms of technical and scale efficiency, the production frontier, and total factor productivity. The results are in Table 5.17.

In comparing all of the four groups, the average technical efficiency is the highest for the group of farmers participating in CRP and off-farm work: the ratio of technical efficiencies between this group is about 1.253 to the (0,0) group. The group only participating in CRP is slightly less technical efficient than the reference group (a ratio is 0.984). On this basis, it appears that participation in CRP has only a modest detrimental effect on technical efficiency. However, that is not the case for the group participating in off-farm work only. The decision to work off the farm appears to improve farm technical efficiency (the ratio is 1.106). One possible explanation might be that for the farm households who participate in the off-farm labor market are more likely to hire professional labor for farming, thus increase the technical efficiency. Our finding is consistent with the finding in Paul and Rehring (2005) and Rehring *et al.* (2005) who utilized a psedo panel data to analyze the off-farm decision of farm productivity.[76]

The story is somewhat different in terms of the scale efficiency and frontier. CRP participation and the off-farm work decisions appear to improve the scale efficiency, but lower the production frontier. Our result suggests that participating in CRP or committing in off-farm work of farm households might operate their farms closer to the technically optimal productive scale. In sum, total factor productivity, as measured by the ratio of T.F.P. relative to the group participating in neither, is down for all three groups as well. For example, the ratios of T.F.P. for the groups who participate only in CRP or only work off the farm are 0.928 and 0.996, respectively, compared to the non-participants. There is an only modest difference for these two groups, but the difference is more pronounced for the group participating in both activities. Part of the reason for this lower TFP for the group participating in both, is that its estimated production frontier lies significantly above the ones for either the CRP participants or the group participating in nether CRP or off-farm work.

[76] Our model differs from these two studies in analyzing the technical efficiency along with the bivariate probit choice model.

Determining the Farm Technical Efficiency

In order to provide insight into the difference in terms of technical efficiency by group, we estimate the technical efficiency equations for each farmer within each group, and discuss the factors determining the technical efficiency and the distributions of the technical efficiency index within the groups. In so doing, we are able to acquire more information to explain the difference between groups in terms of technical efficiency. As a snapshot, we first look at the distribution of the estimated technical efficiency index of each group (Figures 5.10-5.13). The distribution of the technical efficiency is very diverse between groups. For example, the technical efficiency of farmers in the non-participants group is more centralized; while for the group of farmers who commit only to the off-farm job is skewed to the right.

We report the OLS estimation results in Table 5.16 for each group.[77] In general, the specifications of the technical efficiency equations fit the model well, since the adjusted R^2 are reasonable. For example, the adjusted R^2 for each group is 0.415, 0.385, 0.124 and 0.119, respectively. The factors determining the technical efficiency index are operators' characteristics, government payments, and farm characteristics. However, the effects of these variables on technical efficiency are slightly different between groups. Operator's age is negatively related to technical efficiency, with a non-linear effect, for the groups (1-1) and (1-0). However, the effect is positive for group (0-1) and (0-0), although it is not statistically significant. The education level and the farming experience of the operator are also positively related to technical efficiency, except for the group (0-1).

The effects of tenancy and farm size differ between groups. For groups (1-0) and (0-0), farm tenancy is positively related to technical efficiency, but the effect is

[77] The approach we utilize here is similar to the second stage estimation to determine the farm specific attributes in explaining the technical efficiency (Wadud and White 2000; Shafig and Rehman 2000).

negative for group (0-1). The contribution of farm size to the technical efficiency also differs different. For groups (1-1) and (1-0), technical efficiency increases with farm age. However, this effect is negative for the other two groups. Human capital, as reflected in operators' raised on the farm (RAISE_OP) unambiguously increases technical efficiency of all groups. Farm households receiving decoupled payments (AMTA_A) or other government payments (LDP_A) seem to be also more technically efficient.

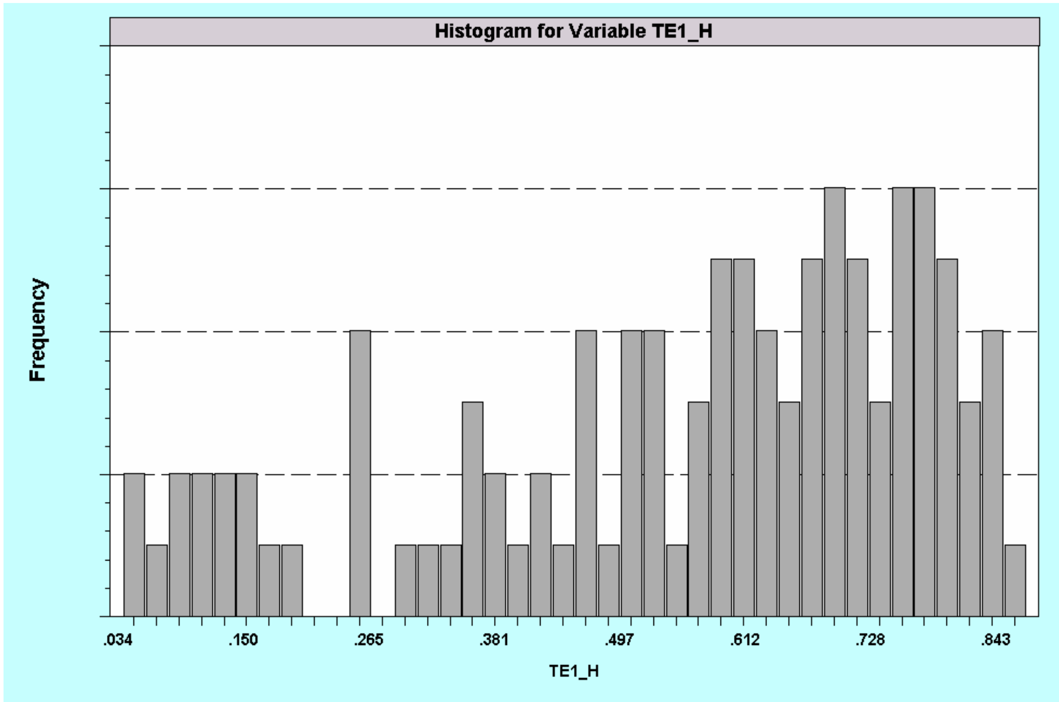

Figure 5.10: Technical Efficiency Index of Group (1,1)

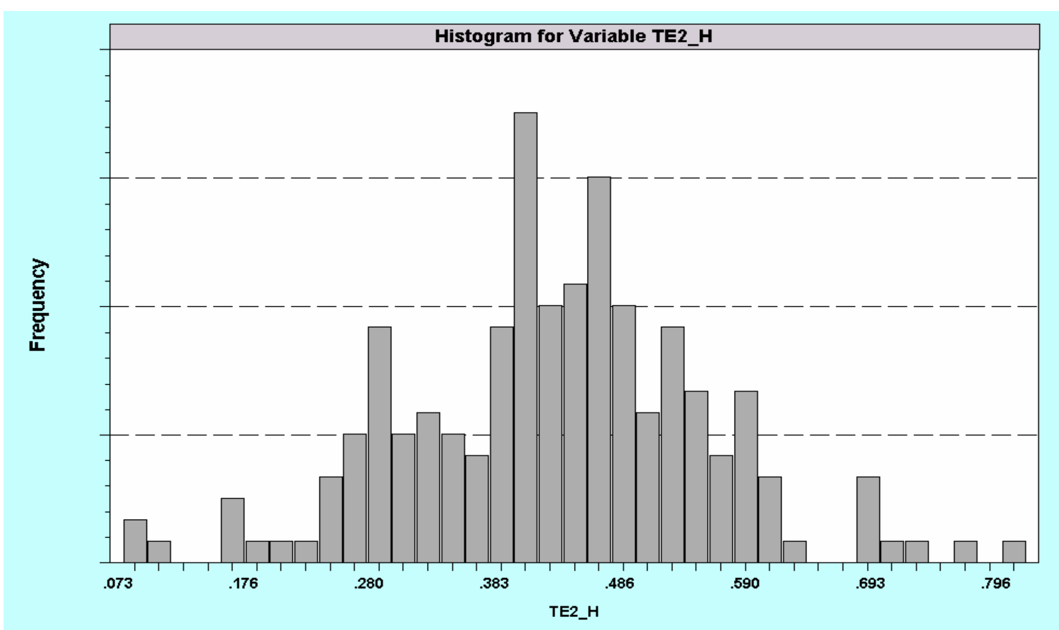

Figure 5.11: Technical Efficiency Index of Group (1,0)

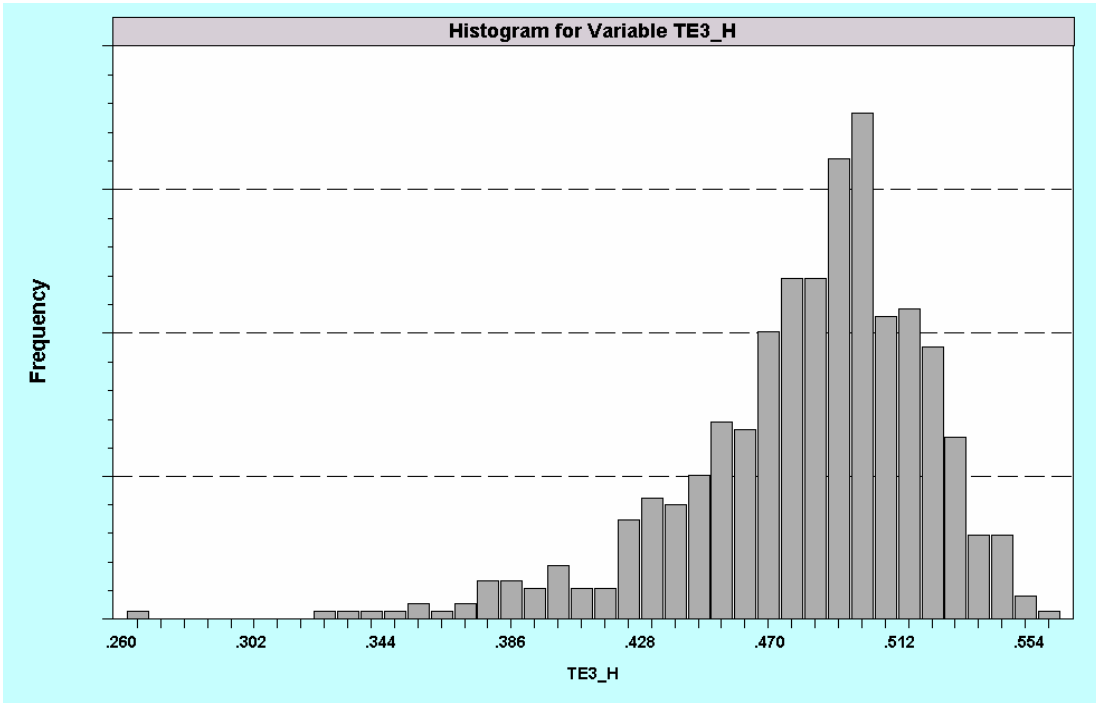

Figure 5.12: Technical Efficiency Index of Group (0,1)

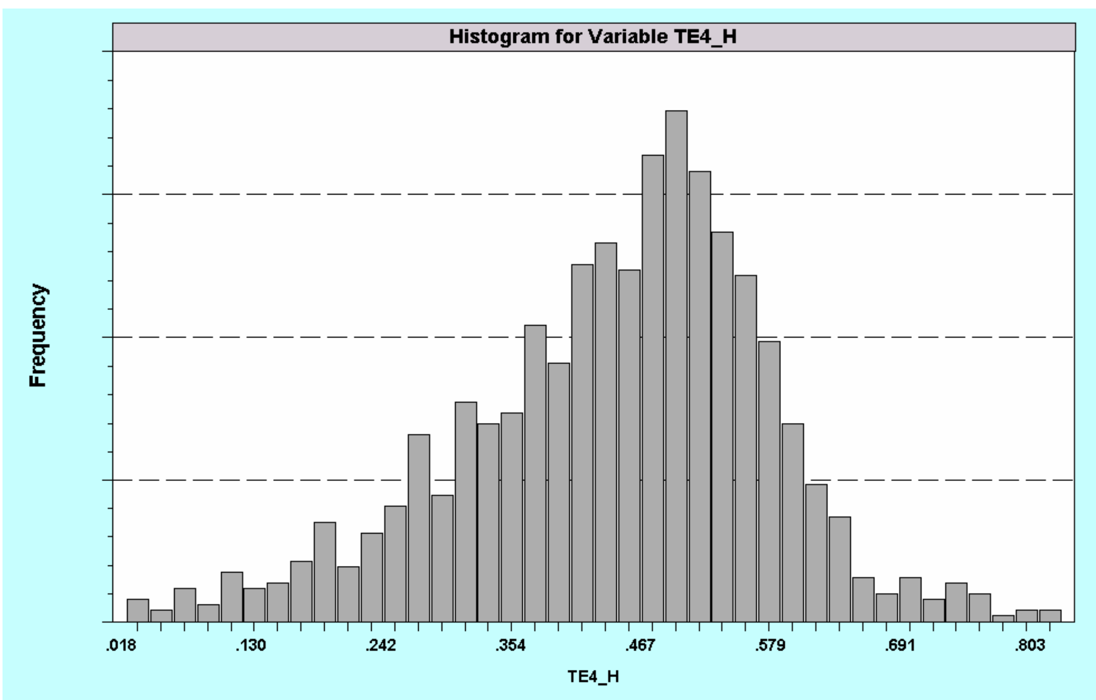

Figure 5.13: Technical Efficiency Index of Group (0,0)

Table 5.16: OLS Estimation for Technical Efficiency Equations

Variable	Coefficient	Std	t-value	Coefficient	Std	t-value
	For CRP=1 and OP=1			**For CRP=1 and OP=1**		
Constant	1.735	0.578	3.001	1.417	0.265	5.354
OP_AGE	-0.060	0.016	-3.756	-0.036	0.008	-4.666
OP_AGESQ	0.538	0.159	3.386	0.338	0.066	5.088
OP_ED_C	0.017	0.068	0.257	-0.058	0.024	-2.444
OP_EDSQ	-0.001	0.003	-0.324	0.002	0.001	2.211
OP_EXP	0.017	0.005	3.421	0.014	0.004	3.488
OP_EXPSQ	0.000	0.000	-2.636	0.000	0.000	-4.474
AMTA_A	0.003	0.002	1.236	0.002	0.001	2.486
LDP_A	0.004	0.001	3.853	0.003	0.001	4.894
TENANCY	-0.016	0.011	-1.371	0.020	0.011	1.795
CROPSIZ1	0.040	0.017	2.295	0.017	0.006	3.036
RAISE_OP	0.049	0.049	0.999	0.075	0.024	3.094
Sample	107			194		
Adjust R^2	0.415			0.385		
	For OP=1			**For CRP=OP=0**		
Constant	0.399	0.039	10.114	-0.020	0.104	-0.193
OP_AGE	0.000	0.001	0.630	0.002	0.002	0.736
OP_AGESQ	-0.008	0.007	-1.121	-0.027	0.019	-1.419
OP_ED_C	0.010	0.005	1.845	0.063	0.014	4.433
OP_EDSQ	0.000	0.000	-1.613	-0.002	0.001	-4.051
OP_EXP	0.000	0.000	1.926	0.000	0.000	-0.781
OP_EXPSQ	0.000	0.000	-1.775	0.000	0.000	0.846
AMTA_A	0.000	0.000	2.697	0.001	0.000	3.334
LDP_A	0.000	0.000	3.233	0.001	0.000	5.207
TENANCY	-0.005	0.001	-4.043	0.005	0.001	3.706
CROPSIZ1	-0.018	0.003	-5.504	-0.023	0.005	-4.378
RAISE_OP	0.003	0.003	0.945	0.014	0.011	1.201
Sample	577			1,150		
Adjust R^2	0.124			0.119		

Variable definitions are listed in Table 2.4 of Chapter 2.

Concluding Remarks

To better understand the interaction between the farm business and the farm household, this chapter identifies those factors that explain participation in these two major non-production related sources of income for farm households: off-farm employment and the Conservation Reserve Program.

It appears that these two decisions by the farm operator are determined jointly, rather than independently or in a sequential fashion. For this reason, we model this joint decision process using a bivariate probit model, and find that a significant correlation between the two decisions of 0.12.

Participating in CRP depends generally on some characteristics of the farm (including the type of farm), the farm operator (including age, experience, and attitudes to risk), land quality, and the circumstances in the local economy. There are also some differences in participation by major ERS production region. As one would expect, decisions to work off the farm are related to many of these same factors, although the direction and magnitude of some of the effects are quite different. It is also true that both decisions are affected by participation in other farm programs.

To determine the level at which farmers participate in these two activities, we also estimate equations for CRP payments, off-farm wage, CRP acreage, and hours worked off the farm. All four equations are estimated for the group of farmers engaged in both activities, while only CRP payments and acreage equations are estimated for the group that participates only in CRP. Equations for the off farm wage and hours worked off the farm are estimated for the groups that work off the farm but do not have land in CRP. In all cases, there was a need to correct for sample selection bias.

As one can imagine, many of the same factors affecting the decisions to participate in off-farm employment and commit land to CRP also affect the level of participation once the commitment is made to the activity. In many cases, the effects are reinforcing, while in others they may seem at odds, although frequently there are plausible explanations. One important finding here is that the acreage committed to CRP is affected by the CRP payment. This is in contrast to much of the existing literature, but it has policy implications. Furthermore, although the elasticities of hours worked with respect to the off farm wage are very low, the cross price elasticities of CRP acreage and hours worked are positive for the group engaged in both activities. Thus, operators receiving higher wages appear to have an incentive both to work less on the farm, but in so doing, they take additional land out of production and commit it to CRP. The flip side of this coin is that as CRP payments increase, the increase in land in CRP reduces the demand for labor on the farm, thus making it available for off-farm purposes.

On this basis of our examination of farm production efficiency, it appears that participation in CRP lowers the technical efficiency, but the effect is minor. We also find that farms of this group operate their farms closer to the technically optimal productive size than the non-participants. But that is not the case for the group participating in both CRP and off-farm work and the group who only participate in the off-farm work. Farm operators who commit to off-farm work seem to have higher technical and scale efficiencies. In sum, that total factor productivity is down significantly for these groups due to the lower production frontiers.

Appendix 5A: Econometric Framework of Second Stage Equations for Other Choice Models

In this appendix, we outline the empirical strategy to estimate the second stage equations based on the multinomial logit (nested multinomial logit) and sequential bivariate probit models for completeness.

Second Stage Analysis of Multinomial and Nested Logit Model

If the multinomial logit or nested multinomial logit model were selected as the appropriate model based on the model selection criterion, it would be necessary to estimate the second stage equations. We first outline the estimation strategy using the multinomial logit model as an example. To estimate these equations, we follow Lee's (1983; 1995) methodology for correcting the selection bias problem under the multinomial logit framework, which is built on the Heckman-Type sample selection framework, but utilizing a transformation method.[78] We introduce his idea in detail below using the regime 1-1 as an example.

In regime 1-1, the farm household is assumed to participate in off-farm work and in CRP. As such, four equations are contained in the second-stage equation system:

(5A.1) $P = \alpha_p' X_p + e_p; \qquad A = \beta_p P + \alpha_a' X_a + e_a$

$$W = \alpha_w' X_w + e_w; \qquad H = \beta_w W + \alpha_h' X_h + e_h$$

Note that if regime 1-1 is chosen, it means that:

(5A.2) $V_{i1} - V_{ij} + (\varepsilon_{i1} - \varepsilon_{ij}) = V_{i1} - V_{ij} + \varepsilon_{i1}^* > 0$

we can rewrite this as:

[78] Besides Lee's approach, Dubin and McFadden (1984) propose an alternative for calculating the selection bias term based on the linearity conditional expectation assumption under multinomial logit model. However, there are two drawbacks of their approach. First, this method can likely be affected by multicolinearity as several bias correction terms may be introduced (Schmertmann 1994). Besides, it is a lot of computation demanding for the asymptotic variance covariance matrix (Maddala 1983). As such, we follow the method proposed by Lee (1983; 1995).

(5A.3) $\varepsilon^*_{i1} > V_{ij} - V_{i1}$

Equation (5A.3) will hold for some strictly increasing function J. That is:

(5A.4) $J(\varepsilon^*_{i1}) > J(V_{ij} - V_{i1})$

Recall that the distribution function of ε^*_{i1} is F(.), which is also equal to the probability that farmer chooses regime 1-1. Define $\tilde{\varepsilon}^*_{i1} = J_\Phi(\varepsilon^*_{i1})$ and $J_\Phi(u) = \Phi^{-1}F(u)$. The function $J_\Phi(u)$ is left-continuous, and strictly increasing. Thus, the transformed random variable, ε^*_{i1}, is easily seen to be a standard normal random variable. Based on this transformation, we can rewrite equation (5A.3) as:

(5A.4) regime 1-1 is chosen if $\tilde{\varepsilon}^*_{i1} > J_\Phi(V_{ij} - V_{i1})$

Now, by assuming a joint normal distribution for the pairs of the random variables, $(e_p, \tilde{\varepsilon}^*_{i1}), (e_a, \tilde{\varepsilon}^*_{i1}), (e_w, \tilde{\varepsilon}^*_{i1}), (e_h, \tilde{\varepsilon}^*_{i1})$, we can apply the standard two-stage sample selection approach proposed by Heckman (1979) to specify the conditional second-stage equations as:

(5A.5)

$$E(P \mid regime1-1) = \alpha_p' X_p + \sigma_{1p} \frac{\phi(J_\Phi(V_{ij} - V_{i1}))}{F(V_{ij} - V_{i1})} = \alpha_p' X_p + \sigma_{1p} \frac{\phi(J_\Phi(V_{ij} - V_{i1}))}{\Pr(regime1-1)}$$

$$E(A \mid regime1-1) = \beta_p \hat{P} + \alpha_a' X_a + \sigma_{1a} \frac{\phi(J_\Phi(V_{ij} - V_{i1}))}{F(V_{ij} - V_{i1})} = \beta_p \hat{P} + \alpha_a' X_a + \sigma_{1a} \frac{\phi(J_\Phi(V_{ij} - V_{i1}))}{\Pr(regime1-1)}$$

$$E(W \mid regime1-1) = \alpha_w' X_w + \sigma_{1w} \frac{\phi(J_\Phi(V_{ij} - V_{i1}))}{F(V_{ij} - V_{i1})} = \alpha_w' X_w + \sigma_{1w} \frac{\phi(J_\Phi(V_{ij} - V_{i1}))}{\Pr(regime1-1)}$$

$$E(H \mid regime1-1) = \beta_w \hat{W} + \alpha_w' X_w + \sigma_{1w} \frac{\phi(J_\Phi(V_{ij} - V_{i1}))}{F(V_{ij} - V_{i1})} = \beta_w \hat{W} + \alpha_w' X_w + \sigma_{1w} \frac{\phi(J_\Phi(V_{ij} - V_{i1}))}{\Pr(regime1-1)}$$

where $\sigma_{1p}, \sigma_{1a}, \sigma_{1w}, \sigma_{1k}$ are the covariance terms between the choice and the second-stage equations. As long as the utility function is specified as the function of explanatory variables of interest, equation (5A.5) can be estimated based on the estimated value of the coefficient from the first-stage multinomial logit model. The procedure for estimating the second-stage equations for the other regimes can be derived in a similar fashion. The details need not be reported here.[5A1]

Lee's approach is not only applicable for the multinomial logit selection case. It can be applied widely to the choice decisions with arbitrary distributed assumptions, and transform it into the standard normal distribution. In so doing, the standard Heckman-type sample selection approach can be applied. For the empirical purposes, this method reduces the computational difficulty (Schmertmann, 1994).

Second-Stage Analysis of the Sequential Bivariate Choice Model

The second stage outcomes of interest are the wage, hour, per-acre payment, and acre enrollment equations. Four possible regimes are realized from the choice outcomes, and the number of equations need to be estimated depends on the observable conditions. The second-stage equations are similar to those for the bivariate probit model. There is a modification, since the difference is that we specify two mutual exclusive choice equations in the second-stage. For regime 1-1 and 1-0,

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[5A1] The estimated variance covariance matrix should be adjusted since the second stage estimation depends on the estimated results of the multinomial logit model (the first stage). The estimated variance covariance matrix can be derived based on the delta method, and shown as (Lee et al 1980; Greene 1998): $V=(X_{j_j}^{*}X_j)^{-1}[\sigma_j^{2}X_j'(I-\rho_j^{2}\Delta_j)X_j+\theta_j^{2}X_j'G_j\nabla G_j'X_j](X_{j_j}^{*}X_j)^{-1}$

where Xj is the matrix of regressors in the second stage equation, including the IMR; σ_j,ρ_j are standard deviation and the correlation coefficient of the second stage equation to the error term of the multinomial choice; Δ_j is the diagnose matrix of $IMR_j^{2}+IMR_j*\Phi^{-1}(\Pr(regm\_j))$; θ_j is the estimated coefficient of IMR; G_j is the partial derivative of IMR to the estimated coefficients of multinomial logit model; and ∇ is the estimated asymptotic variance matrix of the multinomial logit model.

The first term in [.] is used for correcting the heteroscedasticity, similar to the standard sample selection model proposed by Heckman (1979). Along with the first term, the second term focuses on the sample selection correction, although it is more cumbersome than the standard model of Heckman. As long as these two issues are considered, the variance covariance can be adjusted.

the second-stage equations are exactly the same as equation (5.22) and (5.23). However, the second stages for regime 0-1 are (5A.6), compared to equation (5.24):

(5A.6) $E(P \mid I_1 = 0, I_3 = 1) = \alpha_P ' X_P + E(e_P \mid e_1 < -H_1 ' X_1, e_3 > -H_3 ' X_3)$

$$= \alpha_P ' X_P - \sigma_{P1} \frac{\phi(-H_1 ' X_1)}{\Phi(-H_1 ' X_1, H_3 ' X_3, -\rho_{13})} \Phi[\frac{H_3 ' X_3 - \rho_{13} H_1 ' X_1}{\sqrt{1-\rho_{13}{}^2}}]$$

$$+ \sigma_{P3} \frac{\phi(H_3 ' X_3)}{\Phi(-H_1 ' X_1, H_3 ' X_3, \rho_{13})} \Phi[\frac{-H_1 ' X_1 + \rho_{13} H_3 ' X_3}{\sqrt{1-\rho_{13}{}^2}}]$$

$$= \alpha_P ' X_P + \sigma_{P1} \lambda_1 + \sigma_{P3} \lambda_2$$

$$E(A \mid I_1 = 0, I_3 = 1) = \alpha_A ' X_A + E(e_a \mid e_1 < -H_1 ' X_1, e_3 > -H_3 ' X_3)$$

$$= \beta_p \hat{P} + \alpha_A ' X_A - \sigma_{A1} \frac{\phi(-H_1 ' X_1)}{\Phi(-H_1 ' X_1, H_3 ' X_3, -\rho_{13})} \Phi[\frac{H_3 ' X_3 - \rho_{13} H_1 ' X_1}{\sqrt{1-\rho_{13}{}^2}}]$$

$$+ \sigma_{A3} \frac{\phi(H_3 ' X_3)}{\Phi(-H_1 ' X_1, H_3 ' X_3, -\rho_{13})} \Phi[\frac{-H_1 ' X_1 + \rho_{13} H_3 ' X_3}{\sqrt{1-\rho_{13}{}^2}}]$$

$$= \beta_p \hat{P} + \alpha_A ' X_A + \sigma_{A1} \lambda_1 + \sigma_{A3} \lambda_2$$

As in the case of bivariate probit model, the variance-covariance of the estimated second stage equations is incorrect. The correction method is very similar to the bivariate probit choice model.

Appendix 5B: Reconsidering Normality of the Bivariate Probit Model

The intuition behind the normality test based on the non-parametric framework is that if the parametric model is specified correctly, the predicted value of the parametric model should lie in the uniform band of the non-parametric estimation. Although this test had been applied to the binary choice model (Horowitz 1993), to our best knowledge, an application to test the bivariate choice model has not been proposed. As such, we test the bivariate normal assumption of the bivariate probit choice model in two ways. First, we directly apply the methodology proposed by Horowitz (1993) to two binary choice cases (CRP and off-farm labor supply) separately based on the estimates of the bivariate probit model. By comparing the predicted probability of each binary choice model to its non-parametric alternative, we are able to resolve model misspecification issues. In so doing, we are testing two necessary conditions of the bivariate normality assumption: each marginal distribution should be a normal distribution.[5B1] Second, we depict the bivariate kernel density functions based on the estimates of the bivariate probit models as another justification of the bivariate normality assumption.

In Figure 5B.1, the curve with the circle symbol is the cumulative normal distribution of CRP binary choice, and the thin curve is the non-parametric alternative, including the 95% uniform confidence band (the dashed lines) after trimming 1% of the data in tails. The quadratic density is selected as the kernel density with bandwidth of 0.6255.[5B2] By inspection of Figure 5B1, we see that the parametric estimate performs similarly to the non-parametric alternative, particularly for probabilities less

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[5B1] If the bivariate normal case stands, the marginal distribution should be normal. However, the inverse is not necessary true. So this is only a necessary condition to check bivariate normality.

[5B2] The formula of the kernel density is: $G(H_1'X_1) = \frac{\sum_j I_j * K[(H_{1i}'X_{1i} - H_{1j}'X_{1j})/h]}{\sum_j K[(H_{1i}'X_{1i} - H_{1j}'X_{1j})/h]}$, where K(.) is the kernel function; *H'X* is the estimators signal index from the bivariate probit model. The bandwidth (h) is calculated as 0.53288 of this case according to the rule-of-thumb rule.

than 0.50. The two predictions are less consistent for probabilities greater than 0.5, but they still lie within the non-parametric confidence band. In order to acquire information on the distribution, we depict two density functions (univariate normal density and kernel density) based on the CRP choice in Figure 5B.2. The shape of the density distribution is similar, but the mean level is slightly different. On this basis, we might be able to conclude that the binary normality assumption for CRP choice cannot be rejected. This is one of the necessary conditions to ensure the bivariate normality assumption of the bivariate probit model.

Another necessary condition to ensure the bivariate normality assumption is to test if the off-farm labor supply binary choice decision is univariate normal. We apply the same approach as the CRP case to the off-farm labor supply and depict the results in Figure 5B.3 and Figure 5B.4. The curve with the circle symbol of Figure 5B.3 is the cumulative normal distribution of off-farm labor supply binary choice, and the thin curve is the non-parametric alternative, including the 95% uniform confidence band (the dashed lines). The univariate density between parametric and non-parametric estimation are very similar, both in terms of the mean and the shape of the distribution. In general, the parametric model performs well, except it overestimated the participation rate in the low probability area.

Due to the difficulty for deriving the confidence band of the nonparametric bivariate density, we can't test the bivariate probit model against the nonparametric alternative directly. However, it is possible to depict the bivariate density function non-parametrically by applying the bivariate kernel density function estimation. We provide several 3-dimensional graphs, with different angles looking at the distributions from above, of the estimated bivariate kernel density function based on the indexes estimated by the bivariate probit model in Figure 5B.5-5B.8. [5B3]

[5B3] Multivariate quartic kernel function is specified with the bandwidth choice 1.0574 and 0.9561. The

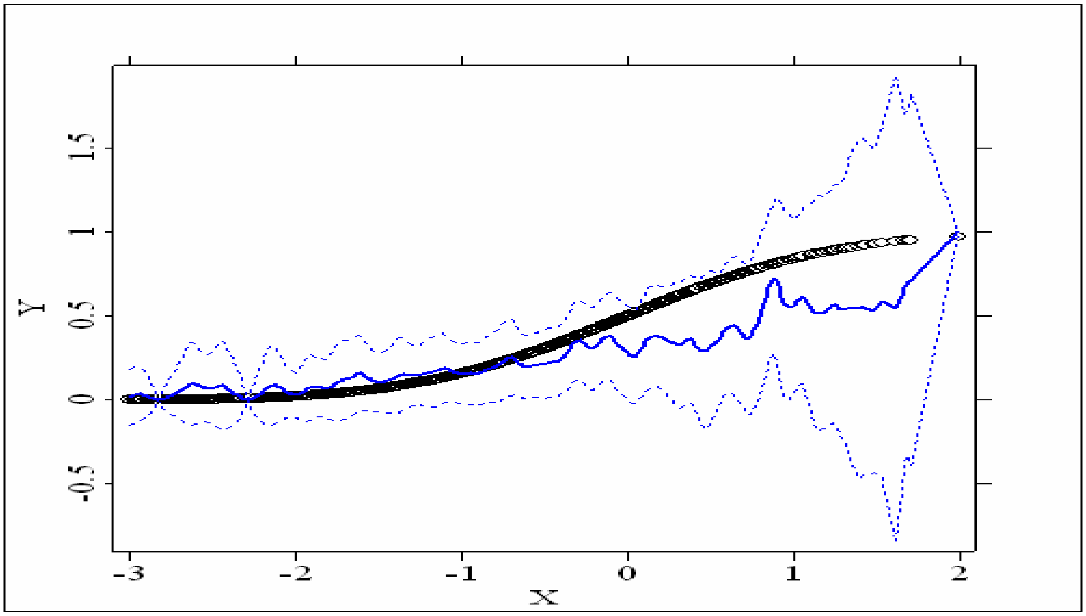

Figure 5B.1: Comparison of the predicted probability for CRP Binary Choice

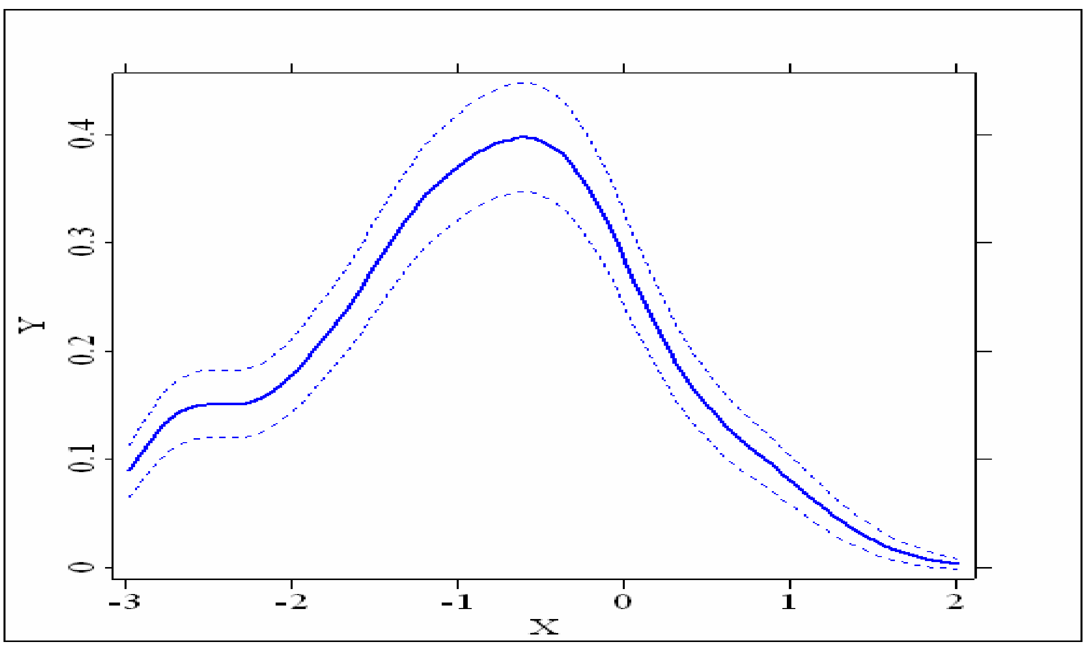

Figure 5B.2: Kernel Density Functions of CRP Binary Choice

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bandwidth is determined based on the rule-of-thumb bandwidth for multivariate density estimation Scott (1992).

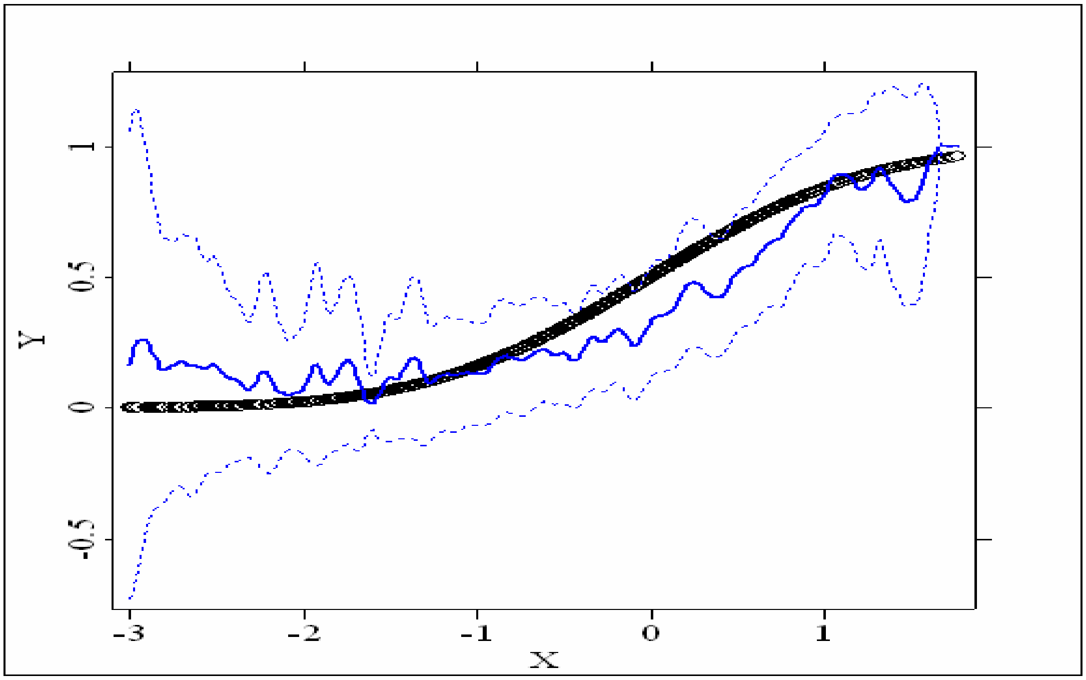

Figure 5B.3: Comparison of the predicted probability for off-farm Binary Choice

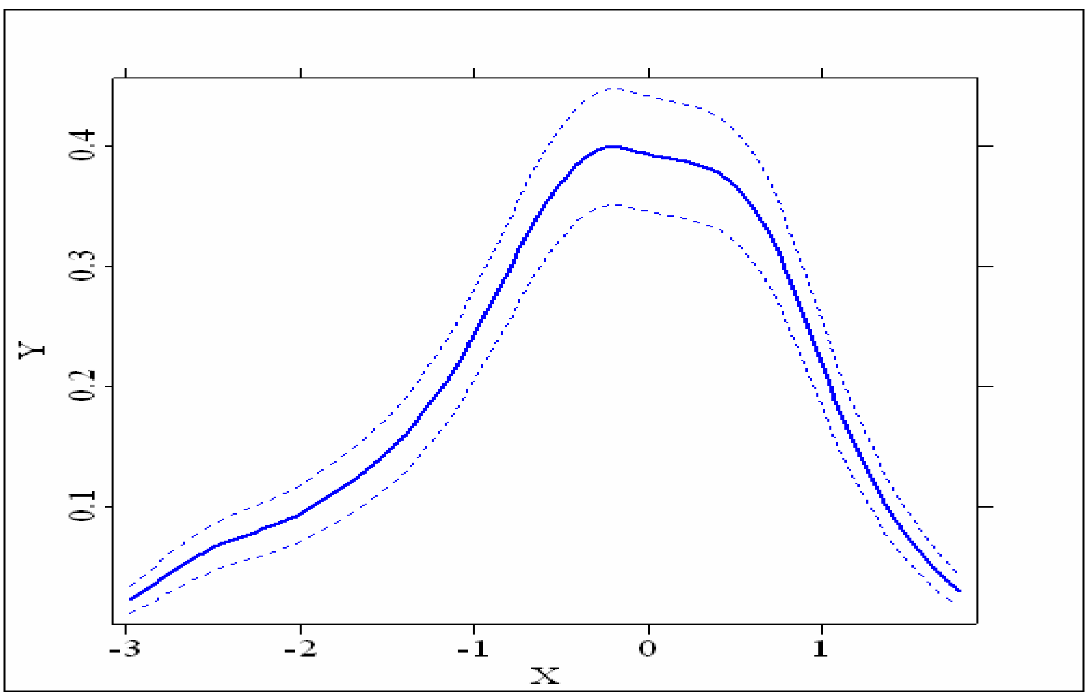

Figure 5B.4: Comparison the density functions of off-farm Binary Choice

In these graphs, the y axis is the signal index of CRP participation and the x axis is the signal index of the off-farm labor decisions; both of them are estimated from the bivariate probit model. The bivariate kernel density is generally symmetric and has the bell shape. These two features are likely consistent with the bivariate normal density function. Mapping the bivariate kernel density to the univariate kernel density, we find that: Figure 5B.7 is consistent with Figure 5B.2. That is, the marginal kernel density is likely to follow the normal distribution; Figure 5B.8 is consistent with Figure 5B.4, the case of off-farm labor decision. Again, we find that the marginal kernel distribution for off-farm labor supply is more likely to follow normal distribution.

In this appendix, we carefully check the model specification issue of the bivariate probit model by comparing the performance against non-parametric alternative. In general, we might be able to conclude that the specification of the bivariate probit choice unlikely to be mis-specified.

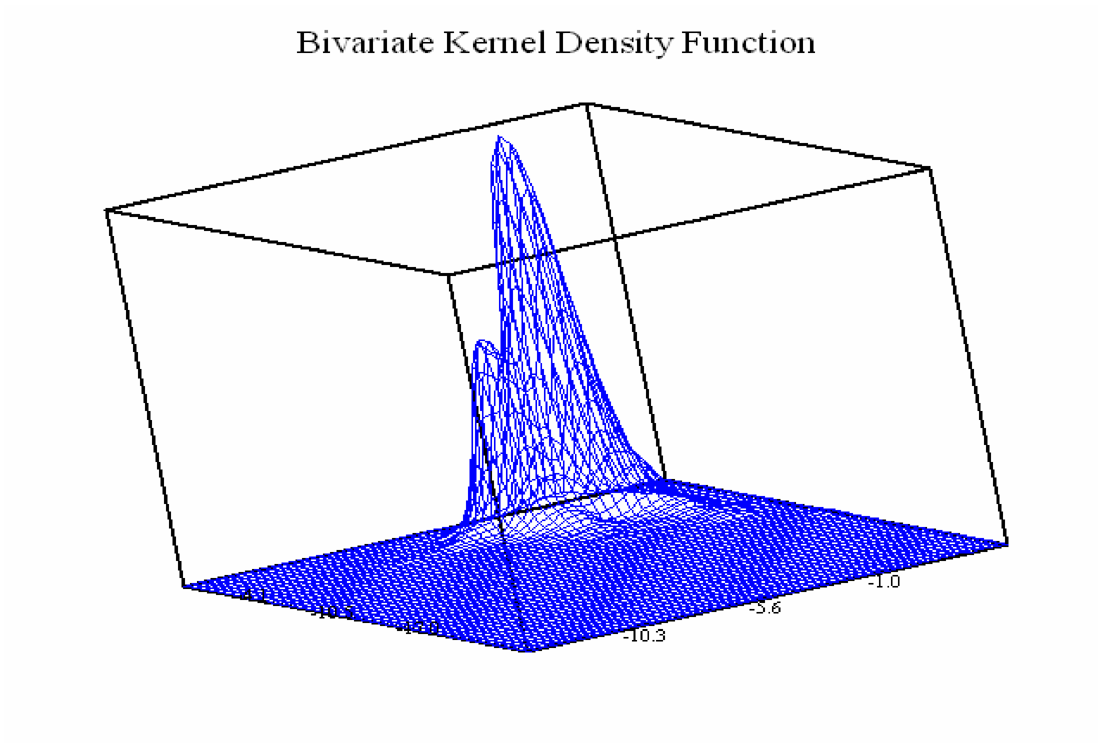

Figure 5B.5: Bivariate Kernel Density Estimation (graph A)

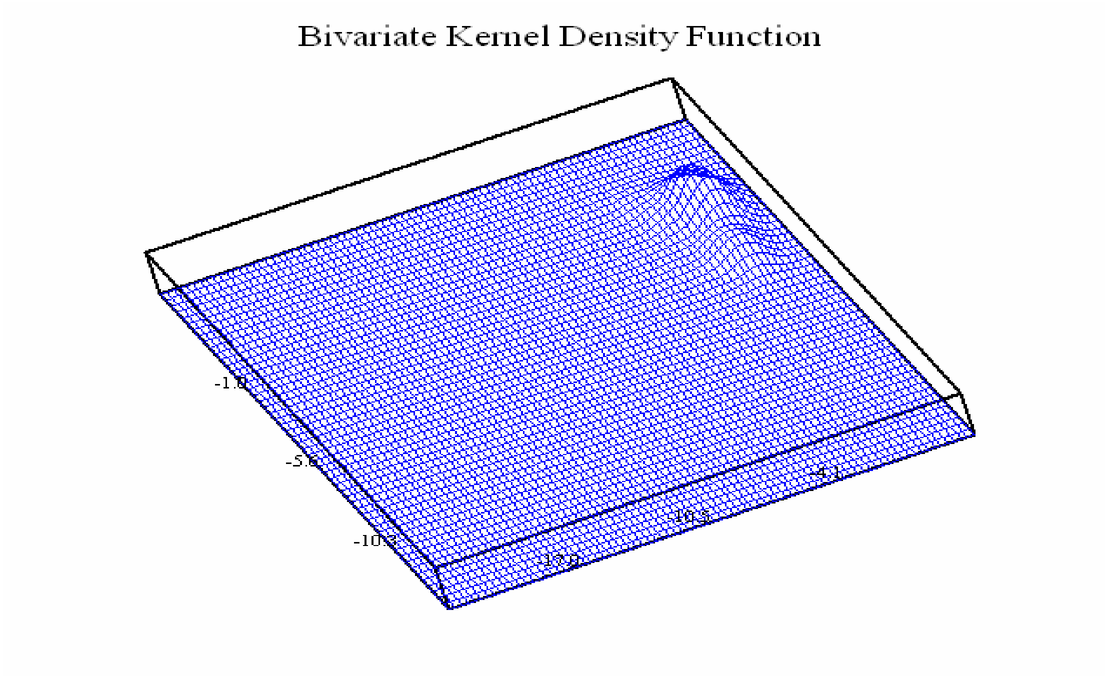

Figure 5B.6: Bivariate Kernel Density Estimation (graph B)

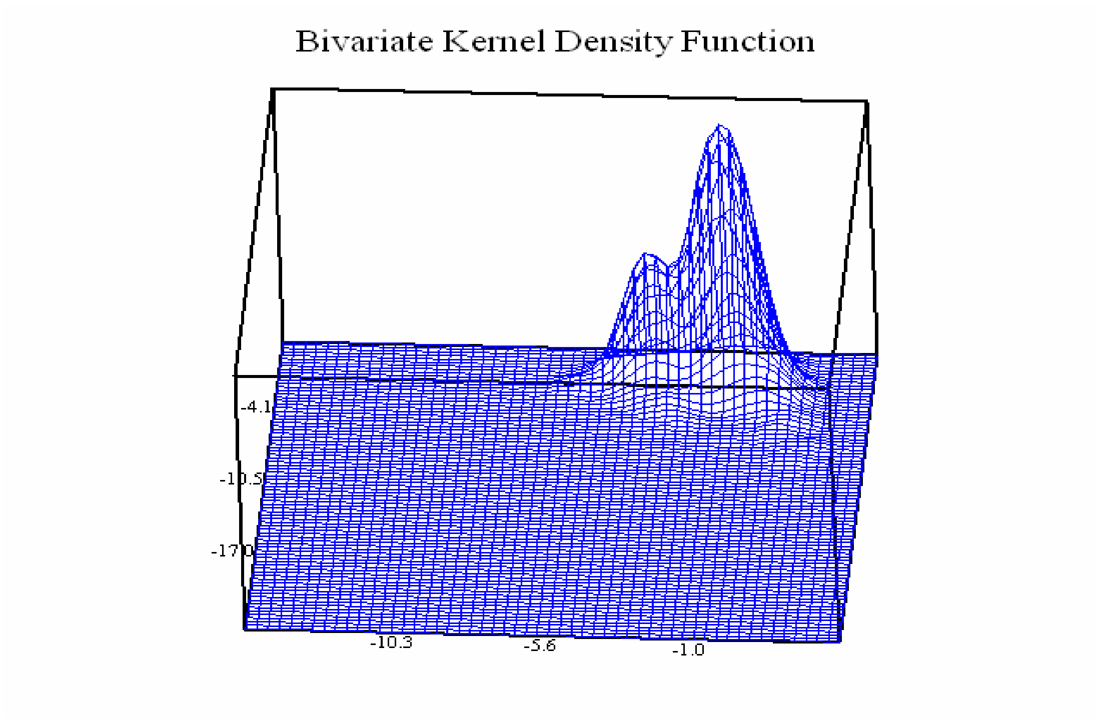

Figure 5B.7: Bivariate Kernel Density Estimation (graph C)

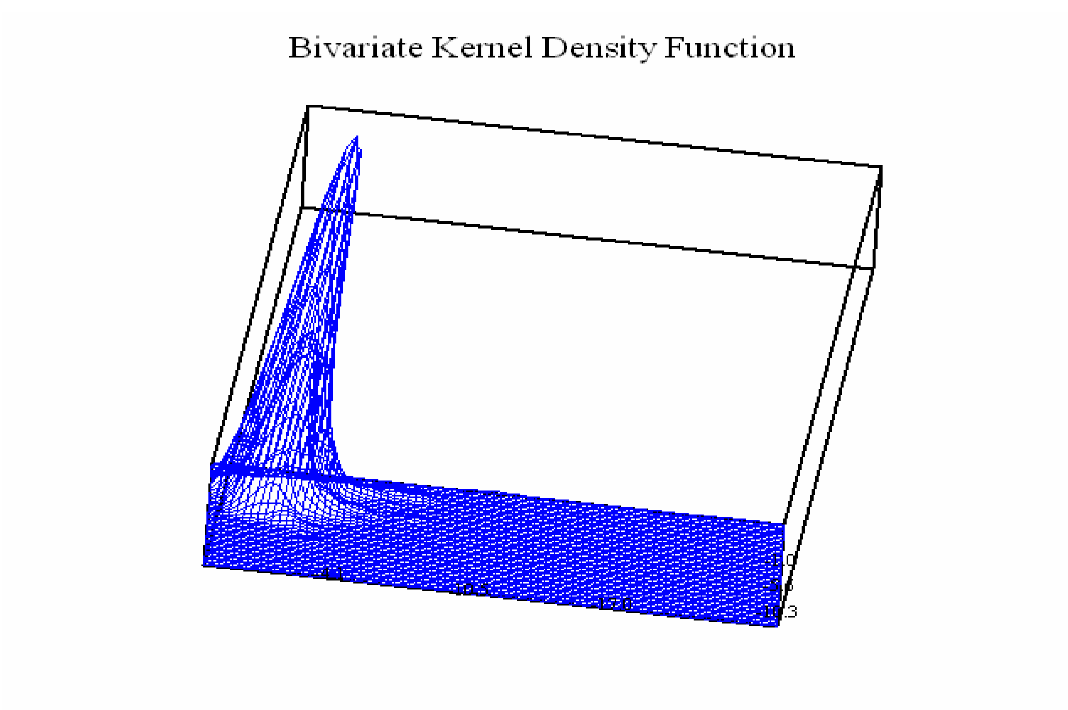

Figure 5B.8: Bivariate Kernel Density Estimation (graph D)

CHAPTER SIX

DETERMINING THE RELATIONSHIPS AMONG DECISION FOR CRP PARTICIPATION AND OFF-FARM LABOR SUPPLY OF FARM OPERATORS AND SPOUSES

Introduction

The focus of Chapter 5 was on decisions to participate in CRP and off-farm work decision by the operator. We extend that analysis and generalize our approach to the case where three decisions are considered by the farm household. Previous research has found that the off-farm work decisions by the farm operator and the spouse are likely to be determined jointly (Huffman and Lange (1989); Kimhi (1994); Lim-Applegate *et al.* (2002); Kwon *et al.* (2002)). Furthermore, Duke (2004) found that the participation decisions by farm households in Delaware's land preservation programs and federal environmental programs, including CRP and EQIP, should be considered jointly.

Although it is important to test jointness when more than two choices are considered, there is a high cost in terms of model estimation because it requires high dimension computations associated with multivariate distributions. In this chapter, we outline a framework for analyzing the multiple decision process and their efforts to the farm production. Our econometric framework is the multiple choice model sample selection model based on Heckman's two-stage method, combined with the endogenous switching regression model. The first step focuses on the estimation of the multiple choice structure; we investigate whether these choices (CRP participation and operator and spouse off-farm work) are joint decisions or are sequential. By modeling these two decision processes, we are able to determine the appropriate choice structure. Given the appropriate choice structure, we focus on the estimations of the off-farm work hours for both the operator and the spouse and the CRP acre enrollment in the second stage. Initially, we introduce the entire econometric framework for the joint decision process, and then we outline the approach for the sequential choice.

Econometric Framework Based on the Joint Decision Process

Similar to the bivariate probit model, we begin by defining each participation decision as a binary probit choice, but we allow for the correlation between choices. The model structure is depicted in Figure 6.1.

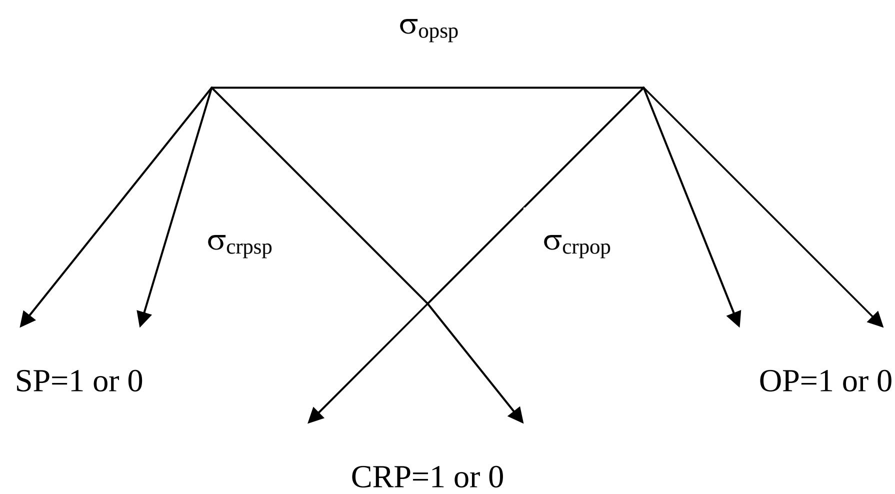

Figure 6.1: Trivariate Probit Model Specification

Each participation decision is assumed to be determined by the net benefit comparison between participation and non-participation of each activity. More precisely, the CRP participation decision is determined by the reservation per acre return to the farm household of retaining the land in production with the government's potential payment for land in the conservation reserve program (CRP). The off-farm job participation decisions of the farm operator and the spouse are determined by comparing the potential off-farm market wage with the shadow values of time in farming.

The specifications for these three equations are as follows:

(6.1) $P^r = A_r X_r + e_r$ and $P^g = A_g X_g + e_g$

(6.2) $W_{op}{}^r = B_{rop} S_{r\,op} + u_{rop}$ and $W_{op}{}^g = B_{gop} S_{gop} + u_{gop}$

(6.3) $W_{sp}{}^r = B_{r\,sp} S_{rsp} + u_{rsp}$ and $W_{sp}{}^g = B_{gsp} S_{gsp} + u_{gsp}$

where P^r and P^g represent the reservation per acre payment, and the potential government per acre payment of CRP; ($W_{op}{}^r$, $W_{op}{}^g$) represent the shadow values of the farming time, and the market off-farm wage of the operator; ($W_{sp}{}^r$, $W_{sp}{}^g$) represent the shadow values of the farming time, and the market off-farm wage of the spouse. The vectors X_r, X_g, S_{rop}, S_{gop}, S_{rsp}, and S_{gsp} are the exogenous variables, and e_r, e_g, u_{rop}, u_{gop}, u_{rsp}, and u_{gsp}, are the random disturbance terms. The latent binary choice variables (I_1*, I_2*, I_3*) of the participation decisions can be defined as:[79]

(6.4) $I_1{*} = P^g - P^r = A_g{}' X_g - A_r{}' X_r + (e_g - e_r) = H_1{}' X_1 + e_1$

$$I_2{*} = W_{op}{}^g - W_{op}{}^r = B_{gop}{}' S_{gop} - B_{rop}{}' S_{rop} + (u_{g\,op} - u_{rop}) = H_2{}' X_2 + e_2$$

$$I_3{*} = W_{sp}{}^g - W_{sp}{}^r = B_{gsp}{}' S_{gsp} - B_{rsp}{}' S_{rsp} + (u_{gsp} - u_{rsp}) = H_3{}' X_3 + e_3$$

If the joint distribution of (e_1, e_2, e_3) follows a trivariate normal distribution following the standard sample selection model (Heckman 1979; Tunali 1986), the joint distribution of these three error structures can be specified as:

[79] For simplicity, subscript 1 refers to the CRP decision; subscript 2 and 3 refers to the off-farm job of the operator and spouse.

$$N\left(\begin{bmatrix}0\\0\\0\end{bmatrix},\begin{bmatrix}1 & \rho_{12} & \rho_{13}\\ \rho_{12} & 1 & \rho_{23}\\ \rho_{13} & \rho_{23} & 1\end{bmatrix}\right),$$

where the correlation coefficient between any two choices (ρ_{ij}) captures the joint nature of any pair of decisions. In reality, it is only the actual binary indicator of each decision, I_i, that is observed. Accordingly, the observation rules for these three latent decision variables are:

$I_i = 1$ (the farmer participates in activity i) iff $I_i^* > 0$; and

$I_i = 0$ (the farmer does not participate in activity i) iff $I_i^* < 0$ i=1,2,3

Given this choice structure, eight potential outcomes (or regimes) can be realized in the data. Based on the observed outcome of each regime, we can define the probability for participating in each regime as a trivariate cumulative normal distribution. For example, the probability of the regime for those households who participate in all three activities can be shown as:

$$P_{11} = \Pr(I_1 = 1, I_2 = 1, I_3 = 1) = \Pr(e_1 > -H_1'X_1, e_2 > -H_2'X_2, e_3 > -H_3'X_3)$$

(6.5)
$$= \int_{-H_1'X_1}^{\infty}\int_{-H_2'X_2}^{\infty}\int_{-H_3'X_3}^{\infty}\phi(I_1, I_2, I_3, \rho_{12}, \rho_{13}, \rho_{23})dI_1 dI_2 dI_3$$

$$= \Phi(H_1'X_1, H_2'X_2, H_3'X_3, \rho_{12}, \rho_{13}, \rho_{23})$$

where $\Phi(.)$ is the cumulative distribution of the trivariate normal distribution.

By defining constants, k_1, k_2 and k_3 as ($2I_1$-1), ($2I_2$-1), and ($2I_3$-1), respectively, we can indicate the regime in which the farm household participates. The generalization of the probability of each regime can be shown as:

$$\Phi[k_1H_1'X_1, k_2H_2'X_2, k_3H_3'X_3, k_1k_2\rho_{12}, k_1k_3\rho_{13}, k_2k_3\rho_{23}]$$

Combining the probability of these eight regimes, the three-choice model can be estimated based on the maximum likelihood method based on the log likelihood function:

$$(6.6) \qquad \log L = \sum_{i=1}^{n} \log\Phi[k_1 H_1' X_1, k_2 H_2' X_2, k_3 H_3' X_3, k_1 k_2 \rho_{12}, k_1 k_3 \rho_{13}, k_2 k_3 \rho_{23}]$$

Although equation (6.6) is a straightforward extension of the bivariate probit model and is theoretically attractive, the computations are demanding. To estimate equation (6.6), we need to evaluate multi-dimensional integrals of normal density functions. Two solutions have been proposed to simplify the computational problem. The first practical solution, a quasi-maximum likelihood approach (QML), is to approximate the multivariate likelihood function with a sequence of bivariate specifications.[80] The second approach is based on simulation techniques, which have facilitated evaluation of the multiple probability integrals and revived interest in earlier likelihood methods. By simulating the multivariate normal probability in the likelihood, this approach provides a practical alternative to numerical evaluation of the probability integrals. Several simulation methods have been advanced recently in the literature, including Stern's method (Stern 1992), a frequency method (Lerman and Manski 1980) and the Geweke-Hajivassiliou-Keane (GHK) simulator.[81] Among all of the simulators, the GHK simulator had proven to be preferred to others (Borsch-Supan and Hajivassiliou 1993; Chen and Cosslett 1998). It is unbiased for any given number of replications, and it generates substantially smaller variances than the frequency simulator and the Stern simulator. Furthermore, it is shown to be the most unambiguously reliable method for simulating normal probabilities (Hajivassiliou, McFadden, and Ruud 1996). Empirically, the GHK simulator has been applied very recently to estimate a censored demand system (Dong *et al.* (2004) and Yen *et al.* (2003)). Based on these evaluations of alternative simulation methods, we also utilize the GHK simulator for

[80] Yen and Lin (2002) applied the same method to a food consumption demand system.
[81] See a comprehensive review in Train (2003) of all available simulators for empirical analysis.

estimating the likelihood function (6.6).

Econometric Framework Based on the Sequential Decision Process

When multiple decisions are discussed, the sequential decision making process is clearly an alternative to the joint decision structure. If we have no prior information about the decision making process of the farm household, it is important to compare both joint and sequential decisions (Lee and Maddala 1994). In so doing, we are able to determine the appropriate model by comparing the differential performance of the two models. We now outline the econometric model of the sequential decision process when three choice decisions are considered.

Although the nested multinomial logit model is perhaps a straightforward way to model the sequential choice, this approach requires normalization for some nodes to be zero for model identification purposes. More importantly, the cost of identification is high as we have seen in the two decision choice case reported in Chapter 5. As such, it is necessary to propose an alternative strategy to model the sequential decision process. Perhaps the easiest way is to simplify the decision tree into only two levels. In contrast to previous chapter, we propose a new strategy for modeling this sequential choice by combining the binary probit model and the multinomial logit model. This can be regarded as the *partial sequential decision process*.

First, we assume that the decision tree can be broken down into two levels: the first level is the binary choice for the decision assumed to be made first; the second level includes the joint decisions for the other two choices. We illustrate our model structure assuming the operators' off-farm decision is considered prior to the others in Figure 6.2.

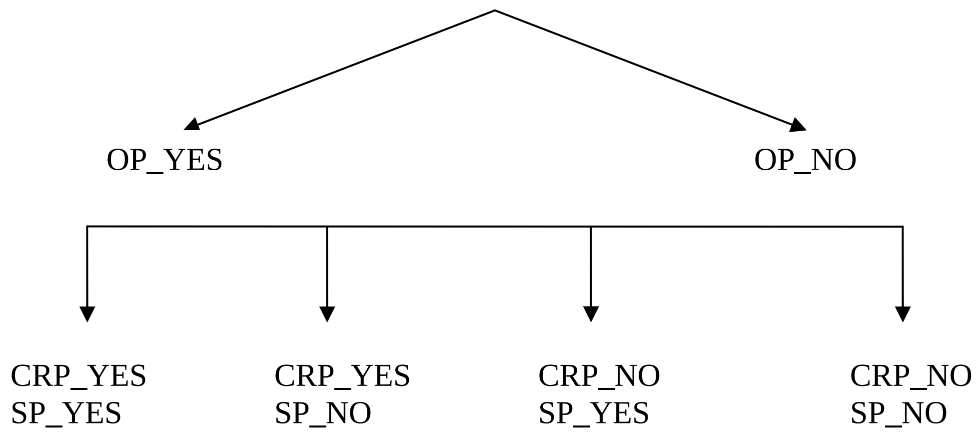

Figure 6.2: Partial Sequential Decision Process (the off-farm decision of the operator is considered prior to other two decisions)

The empirical specification of the first stage is a binary choice decision (the same as equation (6.4)). The second stage choices can be modeled based on the multinomial logit model framework for the entire sample by including the correction term for self-selection calculated from the first stage binary choice as an extra variable.[82]

[82] The reason we focus on the entire sample estimation is as follows: if we focus on the sub-sample given the first stage choice (i.e participants and non-participants of the first choice as two groups), we have to model two multinomial logit models of each group and each of them should include the inverse mills ratio to account for the self-selection problem. There are two potential problems for this approach. First, the formula of the appropriate inverse mills ratio to be included in the multinomial logit model is unknown. One should note that the Heckman type inverse mills ratio requires the bivariate normality assumption between selection equation and the outcome equation. In our case, the first level choice is specified as a binary probit model, while the second level choice is specified as the multinomial logit model, which assumes the error term is Type I extreme value function (McFadden 1974). As such, it is hard to believe that the error terms of two level decisions can be regarded as bivariate normal, and thus the standard approach of Heckman (1979) can't be followed directly. Another disadvantage comes from an empirical concern. One should note that this modeling strategy might be inappropriate if some regimes of the multinomial logit model suffer from small numbers of observations, which might result in singularity of the data matrix, and thus impede the maximum likelihood estimation for the multinomial logit model. Given these difficulties in focusing on the sub-sample, what might be an alternative? If we focus on the entire sample for the second level decision, only one multinomial logit model for the entire sample is estimated. In so doing, the singularity problem can likely be avoided. If the entire sample is used, the self-selection problem can be overcome by utilizing the predicted probability from the first stage binary probit model estimation as the instrumental variables to the second stage choices.

The first binary choice can be shown to be the same as equation (6.4) we defined before: $I_1{}^* = H_1{}' X_1 + e_1$, where I_1 is the indicator observed. I_1=1 iff I_1*>0. There is nothing new in this stage, since this is the standard binary Probit model specification. In the second stage, we assume the multinomial logit model for the entire sample can be specified as:

$$\text{(6.7)} \quad \Pr(U_{is} = 1) = \frac{\exp(r_{ij}{}' w_{ij} + \lambda_j I_1)}{\sum_{j=0}^{3} \exp(r'_{ij} w_{ij} + \lambda_j I_1)} \qquad \text{where j =0,1,2,3}$$

The novelty of equation (6.7) is that we include the binary indicator (I_1) in the multinomial logit model specification. In so doing, we can make the linkage between the first and second level decisions. The estimated parameter λ_j also is the fundamental feature for testing if the sequential choice is specified properly. However, one should find the instrumental variable for the indicator I_1 in order to avoid the endogeneity problem from unobservable correlation. Borrowing an idea from the endogenous treatment effect model, the most straightforward candidate for the instrument would be the predicted probability from the first stage: $\Phi(H_1{}' X_1)$. This instrumental variable is independent of the distribution assumption between equations (6.4) and (6.7), but it is correlated with the binary indicator specified in equation (6.7). Given the specification of the probability for each alternative at the second level, the structural model can be estimated using the full information maximum likelihood (FIML) method. The log likelihood function for the second stage can be shown as:

$$\text{(6.8)} \quad LogL = \sum_{i=1}^{n} \sum_{j=1}^{J} d_{ij} \log \Pr(U_{ij} = 1)$$

where d is the binary indicator for each regime, which is equal to one if the j-th alternative is chosen. The maximum likelihood estimates of equation (6.8) are consistent, albeit not efficient (McFadden 1974).

After estimating equations (6.4) and (6.8) by maximum likelihood estimation, we have to adjust the variance-covariance matrix, since the second level estimation utilized the information (predicted probability) from the first level. We utilize the formula proposed by Murphy and Topel (1985) to calculate the adjusted variance-covariance matrix for the second stage estimators.[83] Murphy and Topel (1985) have shown that if the standard regularity conditions are met for both steps' likelihood functions, then the second step maximum likelihood estimator is consistent and asymptotically normally distributed with asymptotic covariance matrix:

(6.9) $$V_2{*} = V_2 + V_2[CV_1C' - RV_1C' - CV_1R']V_2$$

where V_1,V_2 are the asymptotic variances of the first stage and second stages. If θ_1 and θ_2 represent the consistent estimators of each stage, C and R can be shown as:

$$C = E[(\frac{\partial \log L_2}{\partial \theta_2})(\frac{\partial \log L_2}{\partial \theta_1'})] \qquad R = E[(\frac{\partial \log L_2}{\partial \theta_2})(\frac{\partial \log L_1}{\partial \theta_1'})]$$

Given the maximum likelihood functions of these two steps specified as a binary probit model and the multinomial logit model, one can derive the specific functional form for matrix C and R as follows (Greene 2002b):

(6.10)

$$C = \sum_{i=1}^{n} \begin{bmatrix} (d_{i1} - P_{i1})(\frac{w_i}{\Phi(H_1' X_1)}) \\ (d_{i2} - P_{i2})(\frac{w_i}{\Phi(H_1' X_1)}) \\ (d_{i3} - P_{i3})(\frac{w_i}{\Phi(H_3' X_3)}) \end{bmatrix} * [(d_{i1} - P_{i1})\lambda_1 + (d_{i2} - P_{i2})\lambda_2 + (d_{i3} - P_{i3})\lambda_3]\phi(H_1' X_1) X'_1$$

[83] Another way to deal with the standard error adjustment is to follow the approach of Maddala (1983). However, this approach is more cumbersome than the one Murphy and Topel (1985). Both should generate similar results (Greene 2002a). Thus, we follow the latter for our analysis.

$$R = \sum_{i=1}^{n} \begin{bmatrix} (d_{i1} - P_{i1})(\frac{w_i}{\Phi(H_1' X_1)}) \\ (d_{i2} - P_{i2})(\frac{w_i}{\Phi(H_1' X_1)}) \\ (d_{i3} - P_{i3})(\frac{w_i}{\Phi(H_3' X_3)}) \end{bmatrix} * \{ \frac{(2I_1 - 1)\phi(H_1' X_1)}{\Phi[((2I_1 - 1))H_1' X_1]} X'_1 \}$$

To sum up, we outline the procedure above for estimating the sequential choice model:

(i) Estimate the binary Probit model with the entire sample for the choice which we assume to be considered first.

(ii) Calculate the predicted probabilities based on the estimators of the first step, and include these as new explanatory variables in the multinomial logit model specification.

(iii) Estimate the multinomial logit model with full information maximum likelihood estimation based on the entire sample.

(iv) Calculate the adjusted variance-covariance matrix based on equations (6.9) and (6.10).

Second Stage Analysis Based on the Joint Decision Model [84]

In the second stage, we are interested in estimating equations for the CRP acres enrolled, hours of work off the farm of the operator, and the hours of work off the farm of the spouse. Each equation should correspond to the choice decision we specify above. Based on the theoretical specification, the reduced forms for these equations can be empirically specified, respectively, as:

(6.11) $A = \alpha_a' X_a + e_a$

[84] Based on the empirical results below, the joint decision model ends up preferred to the sequential choice model. Therefore, we limit our attention on the second stage analysis given the joint decision process. Readers who are interested in the second stage analysis of the sequential model we proposed above can refer to Appendix 5A of the previous Chapter.

(6.12) $H_{op} = \alpha_{op}' X_{op} + e_{op}$

(6.13) $H_{sp} = \alpha_{sp}' X_{sp} + e_{sp}$

where X_a, X_{op}, and X_{sp} are vectors of the independent variables for the CRP acres equation, the off-farm hours equation of the operator, and the off-farm hours equation of the spouse, respectively; and α_a , α_{op} and α_{sp} are the vectors of the parameters to be estimated.

Given the choice decisions, equation system (6.11)-(6.13) should be considered differently by regime to account for self-selection bias. Ideally, we should focus on the sub-sample and account for the non-random sampling problem by including the inverse mills ratio for each regime. This approach is a straightforward extension of the bivariate choice sample selection method we discussed in the last chapter. This approach is based on the conditional expectation of equation (6.11)-(6.13) depending on the joint choice decisions. However, it is very computational cumbersome in the case of more than two choices, since the expectation operator of the truncated multivariate normal distribution is complicated due to the consideration of the correlation coefficients.[85] Alternatively, one can focus on the unconditional expectation estimation of equation (6.11)-(6.13) by analyzing the entire sample (Amemiya 1985; Maddala 1983). This full sample approach has not received much attention in empirical studies because the procedure does not necessarily produce more efficient results than those focusing on the sub-sample (Su and Yen 2000). However, Shonkwiler and Yen (1999) argued that in the multiple choice case, this approach might be invaluable due to the different censoring rule of each choice. As such, they propose a simple two stage approach by focusing on the unconditional expectation analysis as the second stage for the multiple-choice sample selection model. The

[85] To the best of our knowledge, the formal of inverse mill ratio had not been studied from previous literature for two choices case.

primary advantage of their method is to simplify the computational task, although their approach suffers from inefficiency, albeit it is consistent. There is little alternative but to follow their approach to estimate the second stage equations.[86]

For each choice, the unconditional expectation of equations (6.11-6.13) can be rewritten (6.11)'-(6.13)' based on the Bayes' rule:

(6.11)' $E(A) = E(A \mid I_1 = 1) * \Pr ob(I_1 = 1) + E(A \mid I_1 = 0) * \Pr ob(I_1 = 0)$

(6.12)' $E(H_{op}) = E(H_{op} \mid I_2 = 1) * \Pr ob(I_2 = 1) + E(H_{op} \mid I_2 = 0) * \Pr ob(I_2 = 0)$

(6.13)' $E(H_{sp}) = E(H_{sp} \mid I_3 = 1) * \Pr ob(I_3 = 1) + E(H_{sp} \mid I_3 = 0) * \Pr ob(I_3 = 0)$

Given the formula for the conditional mean expectations and the predicted probability of program participations considered separately, the unconditional expectations of equations (6.11)'-(6.13)' can be further derived as:

(6.11)'' $E(A) = \Phi(\hat{H}_1' X_1)\alpha_a' X_a + \delta_1 \phi(\hat{H}_1' X_1)$

(6.12)'' $E(H_{op}) = \Phi(\hat{H}_2' X_2)\alpha_{op}' X_{op} + \delta_2 \phi(\hat{H}_2' X_2)$

(6.13)'' $E(H_{sp}) = \Phi(\hat{H}_3' X_3)\alpha_{sp}' X_{sp} + \delta_3 \phi(\hat{H}_3' X_3)$

where $\Phi(.)$ and $\phi(.)$ are the cumulative and density probability function of the normal distribution. The second stage equation system (6.11'-6.13') is the one we are going to estimate.

The second stage equations can be estimated based on a seemingly unrelated regression (SUR) technique suggested by Shonkwiler and Yen (1999). This SUR estimate can generate consistent estimates of the parameters, but the standard errors

[86] Empirically, their approach had been used for correcting the censoring problem in several recent studies of different economic issues. Goodwin, *et al.* (2004) applied this approach to correct for a censoring problem of the CRP acreage enrollment; Yen, Kan, and Su (2002) used it to analyze the fats and oil consumption behavior; Su and Yen (2000) used it for cigarette and alcohol consumption behavior; Earnhart (2003) focused on the transportation problem; and Schmit, *et al.* (2002) extended the method to the panel data case for studying the advertising effect on fluid milk and cheese demand.

are inconsistent since the predicted value of the first stage choice model is unclear. Shonkwiler and Yen (1999) outlined the procedure for adjusting the variance covariance estimates based on the asymptotic theory of Murphy and Topel (1985). However, Shonkwiler and Yen's approach for adjusting the variance covariance is computationally cumbersome and not commonly applied for Heckman type sample selection model.[87] Moreover, the variances of the estimators depend on the conditional mean function (equation (11)), and therefore increase beyond all limits in the absolute size of the signal index of each choice ($H_1'X_1$, $H_2'X_2$, $H_3'X_3$). This appears to be a severe drawback compared to the standard Heckman's sample selection model (Tauchmann 2005). Another alternative for adjusting the variance-covariance estimators is to apply the bootstrap method. For large samples, the bootstrap sampling method is shown to generate the similar result as the one derived from the asymptotic theory (Efron 1987). Furthermore, unless the explanatory variables are specified identically for the selection and second stage equations, the bootstrap standard error matches finite sample variability better than nominal standard error computed by asymptotic covariance matrices (Hill, Adkins, and Bender 2003).[88] Also, the bootstrap method is supported by the asymptotic theory and thus yields the similar results as the asymptotic variance estimates (Efron 1987; Horowitz 2001).[89] Therefore, we apply the bootstrap procedure to estimate the variance covariance matrix for the second stage

[87] When the Heckman-type sample selection model is utilized, White's sandwich variance matrix was suggested to correct the heteroscedasticity and self-selection problems (Lee et al. 1980; Lee 1983; Long and Ervin 2000).

[88] Another advantage for using bootstrap is related to the special sampling design of the ARMS data. An important feature of the ARMS data is relates to the stratified nature of the sampling used to collect the data. So far, two different estimation strategies have been suggested for problems such as this involving stratification. The simplest way involves the delete-group jackknife procedure, whereby the alternative sub-samples are dropped from the analysis (Dubman 2000). However, there is no asymptotic theory behind the delete-group-jackknife procedure and it has been shown to yield inconsistent statistic estimators (Kim et al. 2004). An alternative strategy is to utilize the bootstrap method for estimating the second stage (Goodwin and Mishra 2004; Goodwin, Mishra, and Ortalo-Magne 2003).

[89] Efron (1987) discussed the use of Monte Carlo bootstrapping for obtaining consistent variance-covariance estimates and confident intervals for estimated parameter. They showed that the bootstrap method provided a direct and analytically simplified approach to obtain consistent estimates.

equation system with 500 replications in the empirical section.

To sum up, the two stage procedure we propose to estimate the second stage equation is as follows:

(i) We first estimate the trivariate probit choice model of equation (6.6) with simulated maximum likelihood estimation method based on the GHK simulator.[90]

(ii) We calculate the predicted probability and index of each choice, and then estimate the second stage system (6.11)''-(6.13)'' based on seemly unrelated regression (SUR) method proposed by Shonkwiler and Yen (1999).

(iii) We have to adjust the variance covariance matrix to account for self-selection problem of the error terms based on the bootstrap method.

Empirical Results

Our empirical analysis includes three parts. In the first part, we focus on understanding the interrelationship among CRP participation and the off-farm work decisions of the operator and the spouse. We estimate these three choice decisions both as joint and sequential decisions, and compare this performance in order to determine the appropriate decision making process of the farm household. The results of this part are presented in Tables (6.1-6.5). Given the appropriate decision making process, we focus on the second stage equations in CRP acreage, and hours off the farm work for the operator and spouse (Tables 6.6-6.7). The definitions of the variables used in the analysis are introduced in Table 2.4 on page 21-24 of Chapter 2.

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[90] Shonwiler and Yen (1999) estimate each choice separately by a binary Probit model, which imposes the uncorrelated assumption between choices. However, they mentioned that this simplification is nevertheless consistent, but not efficient (footnote 4, page 974). In order to improve the efficiency, we estimate the choice structure jointly. An analysis of the possible joint correlation is one of the primary objectives of our study, and we are also able to test the independence assumption.

Empirical Results for the Joint Decision Process

In this section, we report the results of the joint decision choice model based on the multivariate probit model framework and estimated with GHK simulators. The explanatory variables we specified in CRP and operator's off-farm work decision equations are the same as the bivariate choice model of previous chapter for comparison purpose. Similar to the operator's work off the farm equation, the spouse's characteristics, farm and family characteristics and location variables are specified for the off-farm work decision of the spouse. The results from the model are very encouraging (Table 6.1).

To begin, let us focus on the correlation coefficients between each pair of choices. From Table 6.1, the CRP participation decision is statistically significant and positively correlated with the off-farm work decisions of both the operator and the spouse. The correlation between CRP and the operator's off-farm work decision is 0.174, and it is consistent with our finding for the two decision case in the previous chapter. The spouse's decision for off-farm work is highly correlated to the operator's working off the farm decision (0.252).[91] Thus, it is perhaps no surprise that there is also correlation between CRP and the spouse's off the farm work decision. However, it is somehow lower (0.116).

These results are strong evidence that the decisions are joint. To justify the joint decision framework rather than the case where these choices are regarded as three single independent decisions, we utilize the likelihood ratio test (LR) to test if the correlation coefficients are jointly equal to zero. The idea behind the test is that: if these decisions can be regarded as independent, the log-likelihood value of the trivariate probit model should be equal to the sum of the log-likelihoods of these three

[91] Our finding is consistent with the finding of the literature focusing on the joint decision for off-farm work between the farm operator and the spouse (Huffman and Lange 1989; Lim-Applegate and Olfert 2002)

binary probit models under the null hypothesis. To implement the LR test, we estimated three independent binary probit models first and calculated the log-likelihood value. Our result shows that the LR test value is 53.86, which is much higher than the critical value under 5% level of significance (7.815). Based on this result, a trivariate probit model is likely more appropriate for reflecting the farm household behavior regarding these three decisions.

Let us now focus on the equations for the CRP participation and the off-farm work decision of the operator. The effects of the explanatory variables in these two equations are similar to the results of the bivariate probit model. In order to avoid unnecessary duplication, we skip the economic interpretation of these effects here. The most interesting results here are the new ones related to the spouse's off farm work. The characteristics of the spouse, family and farm structure, and location affect the choice of the spouse to work off the farm. The spouse who is older and more educated is more likely work off-farm, but the effect is nonlinear in age for the former factor. We also find that the farming experience of the spouse is statistically significant and decreases the likelihood for working off the farm. This might reflect the opportunity cost for off-farm job as we have found for the operator's case. This is perhaps consistent with the negative effect of farm size on the spouse work off-farm. It is also true that the number of children in the farm household is related to the spouse off-farm work decision. Our results show the spouse of farm households with larger numbers of kids is less likely to participate in the off-farm labor market; it is reasonable to predict that the spouse will spend more time for taking care of the family. Finally, the local area around the farm household whose economies have a higher manufacturing index likely provides more opportunities for off-farm work, and this increases the likelihood of the spouse to work off the farm.

Table 6.1: Trivariate Probit Model Estimation

Variable	Coefficient	Std	b/Std
	For OP Choice Equation		
Constant	-3.674	0.699	-5.260
OP_AGE	0.244	0.021	11.719
OP_AGESQ	-2.590	0.183	-14.183
OP_ED_C	0.064	0.015	4.385
OP_EXP	-0.051	0.010	-5.291
OP_EXPSQ	0.001	0.000	4.244
H_SIZE	-0.002	0.034	-0.058
CROPSIZ1	-0.549	0.031	-17.427
RAISE_OP	-0.473	0.104	-4.555
MANUF	0.015	0.006	2.525
TRADE	-0.044	0.015	-3.040
AMTA_A	-0.007	0.003	-2.850
LDP_A	-0.002	0.002	-1.065
RISK	-0.025	0.015	-1.703
NETWORT1	-0.008	0.004	-2.067
SP_HMAK	0.495	0.083	5.981
CROP456	-0.879	0.099	-8.909
REGN3	0.041	0.149	0.273
REGN567	-0.165	0.081	-2.038
TENANCY	-0.045	0.028	-1.596
	For CRP Choice Equation		
Constant	-5.701	1.479	-3.854
OP_AGE	0.031	0.003	9.573
OP_ED_C	0.078	0.016	4.851
LQH_96	0.545	0.232	2.352
LQL_96	-0.959	0.343	-2.793
EQIP	1.110	0.401	2.767
AGDIST	-1.176	0.258	-4.548
EBI	0.055	0.022	2.490
AMTA_A	-0.029	0.005	-5.916
LDP_A	-0.015	0.003	-5.239
RISK	-0.060	0.019	-3.142
CROP456	-1.963	0.262	-7.483
CROPSIZ1	0.226	0.041	5.555
REGN1	0.185	0.110	1.683
REGN567	-0.301	0.148	-2.031
REGN9	1.308	0.274	4.772
URBAN	-0.014	0.002	-7.452

Table 6.1: (Continued)

Variable	Coefficient	Std	b/Std
	For SP Choice Equation		
Constant	-2.845	0.731	-3.890
SP_AGE	0.126	0.027	4.665
SP_AGESQ	-0.002	0.000	-6.919
SP_ED_C	0.160	0.018	9.022
SP_EXP	-0.006	0.003	-1.877
H_SIZE	-0.101	0.034	-2.992
H_SIZE06	-0.263	0.091	-2.895
CROPSIZ1	-0.142	0.055	-2.600
RAISE_SP	0.138	0.071	1.939
MANUF	0.015	0.006	2.691
AMTA_A	-0.004	0.003	-1.243
LDP_A	-0.001	0.002	-0.387
NETWORT1	-0.005	0.005	-0.993
CROP456	-0.880	0.093	-9.449
REGN3	0.141	0.165	0.855
REGN567	0.125	0.076	1.640
	Correlation Coefficients		
RHO(OP,CRP)	0.174	0.055	3.164
RHO(OP,SP)	0.252	0.048	5.275
RHO(CRP,SP)	0.116	0.058	2.001
Log-likelihood	-2,792		
Sample	2,102		
LR Test*	53.86		

**The null hypothesis of LR Test:H_0:RHO(OP,CRP)=RHO(OP,SP)=RHO(CRP,SP)=0*

The critical value is: (x^2 (0.95,3)=7.815)

Variable definitions are listed in Table 2.4 of Chapter 2.

Determining the Sequential Decision Process

To further test the nature of the decision structure, we also estimate two models based on different sequential structures. One of them is that the off-farm decision of the operator is considered prior to other decisions, and the other of them is to consider the spouse's decision of the off-farm work is prior to other decisions.[92] Tables (6.2) and (6.3) contain the estimated results from these two sequential models.

The initial focus of our discussion is on the validation of the sequential structure setting of each model. We evaluate the model performance from two perspectives. First, we test whether there is a linkage between the first (probit) and second stage (multinomial logit) choices. This can be implemented by testing whether the predicted probabilities, estimated from the first stage binary probit model, can be jointly to zero in the second step multinomial logit specification. Our results show that either the operator's decision to work off the farm (Table 6.2) or the spouse's decision to work off the farm (Table 6.3) as the first stage decision is the appropriate first step decision, since the F test values (7.25 and 88.48, respectively) are statistically significant at a 10% level. The second criterion to determine the nature of the sequential structure is based on the non-nested test. Again, we perform the Likelihood Dominance Criterion (LDC) test for model comparison which we have introduced in previous chapter. Our result shows that the test value is 60.458, which is greater than the critical value (1.766) in Table (6.4). Thus, if we have to choose between these two sequential structures, the sequential model assuming the off-farm work decision of the operator is considered first is preferred to the other specification.

[92] In reality, the alternative that CRP decision might be also possible to made first prior to the operator's and spouse's working decision. However, our estimation suffers from the singularity problem due to the few observations and thus impedes the estimation procedure of the multinomial logit model. We are not able to include this sequential decision model in this study.

Table 6.2: Sequential Choice Model_ If OP is chosen first

Variable	Coefficient	Std	t-value
	First Stage Estimation Probit Model		
Constant	-3.405	0.694	-4.909
OP_AGE	0.242	0.023	10.659
OP_AGESQ	-2.557	0.213	-12.024
OP_ED_C	0.052	0.014	3.633
OP_EXP	-0.050	0.010	-5.200
OP_EXPSQ	0.001	0.000	3.862
H_SIZE	0.004	0.030	0.125
CROPSIZ1	-0.543	0.065	-8.405
RAISE_OP	-0.477	0.096	-4.975
MANUF	0.015	0.005	2.720
TRADE	-0.049	0.015	-3.343
AMTA_A	-0.007	0.003	-2.643
LDP_A	-0.002	0.002	-1.097
RISK	-0.022	0.015	-1.488
NETWORT1	-0.007	0.005	-1.341
SP_HMAK	0.289	0.075	3.831
CROP456	-0.841	0.096	-8.720
REGN3	0.055	0.148	0.369
REGN567	-0.172	0.077	-2.237
TENANCY	-0.043	0.018	-2.412
Log_likelihood	*-1024*		
Predicted Rate	*73%*		
	Second Stage Multinomial Logit Model		
	For SP=1 Only		
OP_AGE	-0.090	0.030	-3.040
OP_ED_C	0.056	0.082	0.686
LQH_96	-0.419	0.567	-0.739
LQL_96	-1.152	0.658	-1.752
EQIP	1.068	2.481	0.431
AGDIST	0.795	0.467	1.702
EBI	-0.132	0.028	-4.711
AMTA_A	-0.018	0.027	-0.672
LDP_A	-0.005	0.014	-0.338
RISK	-0.004	0.086	-0.043
CROP456	-2.522	0.632	-3.991
CROPSIZ1	-1.261	1.003	-1.257
REGN1	0.364	0.295	1.236
REGN3	0.611	0.854	0.716
REGN567	-0.433	0.520	-0.833
REGN9	-1.468	1.636	-0.897
URBAN	-0.007	0.005	-1.397
MANUF	0.012	0.026	0.471
SP_AGE	0.675	0.087	7.734
SP_AGESQ	-0.007	0.001	-8.438
SP_ED_C	0.298	0.052	5.673
SP_EXP	-0.049	0.020	-2.403
H_SIZE06	-0.524	0.325	-1.611
NETWORT1	-0.025	0.078	-0.321
PROB_OP	-5.380	1.223	-4.398

Table 6.2: (Continued)

Variable	Coefficient	Std	b/Std
		For CRP=1 Only	
OP_AGE	0.081	0.024	3.367
OP_ED_C	0.295	0.072	4.069
LQH_96	-1.202	0.685	-1.754
LQL_96	-4.913	1.147	-4.284
EQIP	2.461	2.236	1.100
AGDIST	-2.179	1.357	-1.606
EBI	-0.017	0.040	-0.424
AMTA_A	-0.045	0.019	-2.374
LDP_A	-0.029	0.011	-2.535
RISK	-0.181	0.060	-3.022
CROP456	-4.750	1.751	-2.712
CROPSIZ1	0.110	0.169	0.647
REGN1	1.288	0.309	4.169
REGN3	1.248	0.459	2.719
REGN567	-0.692	0.394	-1.757
REGN9	1.299	1.517	0.857
URBAN	-0.021	0.006	-3.539
MANUF	-0.015	0.018	-0.825
SP_AGE	-0.096	0.083	-1.167
SP_AGESQ	0.001	0.001	0.951
SP_ED_C	-0.137	0.060	-2.275
SP_EXP	-0.004	0.013	-0.343
H_SIZE06	-0.268	0.449	-0.598
NETWORT1	0.013	0.012	1.120
PROB_OP	-0.229	1.245	-0.184

Table 6.2: (Continued)

Variable	Coefficient	Std	b/Std
	For CRP=SP=1 Only		
OP_AGE	-0.051	0.030	-1.714
OP_ED_C	0.115	0.072	1.594
LQH_96	1.043	0.632	1.650
LQL_96	-1.521	1.049	-1.450
EQIP	2.151	2.844	0.756
AGDIST	-1.168	0.739	-1.582
EBI	-0.057	0.034	-1.686
AMTA_A	-0.075	0.025	-3.014
LDP_A	-0.033	0.013	-2.535
RISK	-0.057	0.076	-0.751
CROP456	-6.063	1.323	-4.583
CROPSIZ1	-0.402	0.636	-0.633
REGN1	0.355	0.303	1.171
REGN3	0.516	0.724	0.712
REGN567	-1.711	0.582	-2.942
REGN9	0.002	1.505	0.001
URBAN	-0.032	0.006	-5.182
MANUF	0.058	0.024	2.380
SP_AGE	0.348	0.077	4.539
SP_AGESQ	-0.004	0.001	-5.597
SP_ED_C	0.152	0.060	2.538
SP_EXP	-0.040	0.016	-2.488
H_SIZE06	-0.718	0.332	-2.164
NETWORT1	0.012	0.010	1.270
PROB_OP	-3.879	0.505	-7.682
Loglikelihood	*-1,670*		
*F test**	7.25		

Standard error is adjusted with Murphy & Topel's method

** The null hypothesis: 3 terms of PROB_OP are jointed equal to zero*

critical value x2(0.95,3)=7.81; x2(0.90,3)=6.25

Variable definitions are listed in Table 2.4 of Chapter 2.

Table 6.3: Sequential Choice Model (If SP is chosen first)

Variable	Coefficient	Std	t-value
	First Stage Estimation Probit Model		
Constant	-3.042	0.650	-4.680
SP_AGE	0.128	0.023	5.427
SP_AGESQ	-0.002	0.000	-7.934
SP_ED_C	0.146	0.017	8.728
SP_EXP	-0.006	0.003	-1.913
H_SIZE06	-0.334	0.078	-4.274
CROPSIZ1	-0.146	0.054	-2.715
MANUF	0.015	0.005	2.944
AMTA_A	-0.004	0.003	-1.362
LDP_A	0.000	0.002	-0.277
NETWORT1	-0.006	0.005	-1.246
CROP456	-0.890	0.084	-10.601
REGN3	0.138	0.150	0.923
REGN567	0.166	0.075	2.203
Log_likelihood	*-1037*		
Predicted Rate	*72%*		
	Second Stage Multinomial Logit Model		
	For OP=1 Only		
OP_AGE	0.297	0.045	6.581
OP_AGESQ	-3.336	0.472	-7.071
OP_ED_C	0.068	0.029	2.345
OP_EXP	-0.041	0.020	-2.110
OP_EXPSQ	0.000	0.000	1.038
H_SIZE	-0.070	0.057	-1.233
CROPSIZ1	-1.823	0.212	-8.606
RAISE_OP	-0.938	0.190	-4.939
MANUF	0.028	0.012	2.269
TRADE	-0.174	0.031	-5.684
URBAN	0.006	0.004	1.737
AMTA_A	-0.005	0.005	-0.909
LDP_A	-0.003	0.003	-0.919
RISK	-0.004	0.029	-0.151
NETWORT1	-0.028	0.014	-2.057
SP_HMAK	0.605	0.158	3.829
CROP456	-1.469	0.225	-6.536
REGN1	-0.093	0.197	-0.469
REGN3	0.632	0.361	1.750
REGN567	-0.300	0.168	-1.784
REGN9	-1.641	0.639	-2.568
TENANCY	-0.136	0.062	-2.185
LQH_96	0.419	0.406	1.032
LQL_96	-0.693	0.453	-1.531
EQIP	0.361	1.243	0.290
AGDIST	-0.289	0.330	-0.875
EBI	-0.019	0.016	-1.170
PROB_SP	0.311	0.532	0.585

Table 6.3: (Contined)

Variable	Coefficient	Std	b/Std
	For CRP=1 Only		
OP_AGE	-0.008	0.073	-0.110
OP_AGESQ	0.603	0.648	0.931
OP_ED_C	0.156	0.044	3.521
OP_EXP	0.105	0.036	2.915
OP_EXPSQ	-0.002	0.001	-3.290
H_SIZE	-0.049	0.117	-0.419
CROPSIZ1	0.217	0.120	1.807
RAISE_OP	-0.336	0.355	-0.946
MANUF	0.034	0.017	1.997
TRADE	-0.258	0.054	-4.783
URBAN	-0.003	0.006	-0.579
AMTA_A	-0.041	0.018	-2.293
LDP_A	-0.029	0.010	-3.086
RISK	-0.050	0.047	-1.065
NETWORT1	0.009	0.044	0.212
SP_HMAK	-0.290	0.280	-1.035
CROP456	-4.080	0.923	-4.419
REGN1	0.072	0.289	0.248
REGN3	1.217	0.383	3.179
REGN567	-0.341	0.381	-0.895
REGN9	0.397	1.376	0.289
TENANCY	0.034	0.051	0.669
LQH_96	1.753	0.663	2.645
LQL_96	-3.572	1.153	-3.099
EQIP	1.934	1.295	1.494
AGDIST	-1.234	0.654	-1.887
EBI	-0.001	0.034	-0.028
PROB_SP	-0.588	0.780	-0.753

Table 6.3: (Continued)

Variable	Coefficient	Std	b/Std
	For OP=CRP=1 Only		
OP_AGE	0.296	0.080	3.676
OP_AGESQ	-3.161	0.809	-3.907
OP_ED_C	0.153	0.043	3.533
OP_EXP	-0.025	0.028	-0.881
OP_EXPSQ	0.000	0.001	0.367
H_SIZE	0.030	0.089	0.340
CROPSIZ1	-0.360	0.728	-0.495
RAISE_OP	-1.479	0.285	-5.183
MANUF	0.047	0.017	2.684
TRADE	-0.205	0.054	-3.821
URBAN	-0.021	0.005	-4.059
AMTA_A	-0.085	0.019	-4.517
LDP_A	-0.029	0.009	-3.304
RISK	-0.164	0.045	-3.666
NETWORT1	0.019	0.047	0.417
SP_HMAK	-0.004	0.286	-0.012
CROP456	-8.916	3.516	-2.536
REGN1	1.007	0.268	3.753
REGN3	0.319	0.553	0.577
REGN567	-1.720	0.437	-3.937
REGN9	0.339	0.790	0.429
TENANCY	0.057	0.048	1.185
LQH_96	-0.160	0.634	-0.253
LQL_96	-1.416	0.835	-1.696
EQIP	0.280	2.871	0.097
AGDIST	-3.075	1.530	-2.010
EBI	0.001	0.036	0.038
PROB_SP	-1.734	0.905	-1.916
Loglikelihood	*-1,622*		
*F test**	88.48		

Standard error is adjusted with Murphy & Topel's method

** The null hypothesis: 3 terms of PROB_SP are jointed equal to zero*
critical value x2(0.95,3)=7.81; x2(0.90,3)=6.25
Variable definitions are listed in Table 2.4 of Chapter 2.

As we have discussed in the two choice case earlier, one of the primary criticisms of the multinomial logit model is the IIA property, which might imply that the relative ratio of participation of any two pair alternatives is independent from other alternatives. This is a strong assumption and it can be tested by using the Haussman-Wu test (Greene 2002b). Our test results show that the IIA assumption is rejected.[93] Since the IIA property should be one of the model selection criterions for justifying the sequential choice model, we conclude that the partial sequential decision model is not appropriate to capture a three choice decision making process. This result is also consistent with our finding in last chapter when two decisions are considered: Joint decision is preferred to the sequential choice process.

Table 6.4:Testing for Sequential Choice Models

	Likelihood Dominant Criterion Test_Sequential Decision		
	Different in LogL	Test Value	Model Selection
OP vs SP first	60.458	1.766	**OP first**
	IIA Test for Second Stage Multinomial Logit Model		
Deleted Group		Test Value*	Result
(0,0) of OP Model		227	**Reject IIA**

** the critical value x^2 (0.95,1) is equal to 37.65*

[93] If the non-participant group (not participate in either CRP or off-farm decision of the spouse) was eliminated from the sample, the Haussman-Wu test value was 227, which is greater than the critical value (x^2(0.95,1)=37.65). As such, the IIA property was rejected (See Table 6.4).

Testing for Endogeneity of the Choice Equations

Another issue to be discussed in model specification is the endogeneity issue. Indeed, one might argue that some variables specified of the three choice equations as the explanatory variables might be endogenous to the choices. Since the specifications of the CRP participation and the off-farm work decision of the operator are the same as the two choice case, and we have implemented the endogeneity test for these two equations in previous chapter, we focused on the endogeneity test to see whether two explanatory variables (AMTA_A) are endogenous to the spouse's decision for off-farm work based on the framework of Smith and Blundell (1986). Since the detail of the test can be found in previous chapter, we skip the content here to avoid duplication. The test result is presented in Table (6.5). The result is somehow encouraging, since the two variables are not statistically endogenous to the spouse' off-farm decision.

Table 6.5: Exogeneity Test for SP Equation

Variables	T Value	P-Value
AMTA_A	-1.282	0.200

*** Note: Calculated based on Smith & Blundell (1986)*

Empirical Results of the Second Stage System

The second stage equation system of interest (Table 6.6) contains equations for the acres enrolled in CRP, the hours worked off the farm by the operator and the spouse. In contrast to the procedure we discussed in previous chapters, we estimate these three equations directly by specifying the observed CRP per acre payment, off-farm wage of the operator and spouse as one of the explanatory variables in the second stage equations, without estimating these three price equations and using the predicted prices as instrumental variables in the acre and hours equations.[94] In so doing, we are

[94] One might argue the endogeneity problem between quanity and price variables in our specification.

able to derive the own and cross-price effect or elasticity.

For the perspective of model specification, the self-selection problem is analyzed by testing if the coefficients of the predicted normal density function of each equation are jointly equal to zero. The F test value is 127, which is greater than the critical value under the 5% level of significance (7.81). As such, we are able to conclude that the sample selection problem exists in our data.

The explanatory variables which are statistically significant in the operator's hour equation are the off-farm working experience, farm size, risk preference, and the employment structure of the local economy. We have interpreted the economic intuition of these factors in the last chapter, and ignore the duplication context here. The CRP acres enrolled are determined by the operator's characteristics, farm and family structure, environmental quality, and the local economy conditions. The explanatory variables we specify in this equation are identical to the one of the bivariate choice case. The interesting case here is the factors affecting the hours working off the farm of the spouse. The spouse performs more non-farm labor as she ages, but at a decreasing rate. Off-farm labor supply of the spouse is negatively and significantly affected by both the farm size, tenancy system of the farm, and the government payments. Interestingly, the risk preference of the operator also affects the labor supply of the spouse. If the operator is more risk averse, the off-farm labor supply of the spouse increases. This might be true since the more risk averse operator would like to participate in the off-farm job, and thus increases the labor supply of the operator. The positive correlation of the off-farm participation decisions between the

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However, Shonkwiler and Yen (1999)'s approach is not appropriate if instrumental variables (predicted price variables) are used in the second stage equations. The reason is that the traditional IV approach is validated if and only if the estimated second stage system is linear (equation (11)). Unfortunately, the second stage system is a non-linear system in our case. If the predicted price variables are served as IV of equation (11), their approach would yield inconsistent estimates (West and William III 2004, page 556; Bound *et al.* 1995).

operator and the spouse is likely to increase the off-farm labor supply of the spouse.

Table 6.6: Second Stage System Estimation

Variable	Coefficient	Std	t-value
	OP Hour Equation		
CDF_OP	4.714	717.550	0.007
OP_AGE	30.554	31.045	0.984
OP_AGESQ	-342.480	314.040	-1.091
OP_EXP_F	-0.161	0.106	-1.518
OP_RAISE	86.912	116.150	0.748
CROPSIZ1	-489.169	73.437	-6.661
TENAN	2.842	21.687	0.131
AMTA_A	-2.502	2.573	-0.972
LDP_A	-1.153	1.508	-0.764
RISK	-40.243	13.579	-2.964
TRADE	2.688	11.146	0.241
MANUF	21.989	5.423	4.055
UNEMP	-21.415	14.714	-1.455
REGN3	-929.590	178.140	-5.218
PDF_OP	391.627	171.010	2.290
LGWAGEOP	615.869	23.874	25.797
LGPCRP	20.689	19.222	1.076
LGWAGESP	-33.860	21.846	-1.550
R^2	0.400		
Adjusted R^2	0.395		
	CRP Acreage Equation		
CDF_CRP	286.836	205.970	1.393
OP_EXP	-4.227	2.275	-1.858
OP_EXPSQ	0.158	0.051	3.118
OP_AGE	1.981	5.664	0.350
OP_AGESQ	-60.312	45.617	-1.322
LQH	-520.082	50.415	-10.316
LQM	-401.778	60.562	-6.634
REGN1	-4.969	18.369	-0.271
REGN3	105.273	48.079	2.190
RN567	150.071	59.523	2.521
REGN9	-15.975	26.179	-0.610
CROP17	129.170	26.413	4.890
CROPSIZ1	100.462	149.650	0.671
AMTA_A	-3.279	1.319	-2.486
EQIP	-310.964	87.001	-3.574
MANUF	-5.796	1.033	-5.609
HSIZE	-14.887	7.130	-2.088
PDF_CRP	87.900	38.274	2.297
LGWAGEOP	3.765	0.944	3.989
LGPCRP	68.107	3.977	17.123
LGWAGESP	0.155	0.995	0.156
R^2	0.685		
Adjusted R^2	0.682		

Table 6.6: (Continued)

Variable	Coefficient	Std	b/Std
	Hour_SP Equation		
CDF_SP	-703.435	561.800	-1.252
SP_AGE	103.632	23.276	4.452
SP_AGESQ	-1.253	0.289	-4.341
SP_RAISE	-61.935	49.806	-1.244
LDP_A	-1.831	0.856	-2.139
CROPSIZ1	-223.764	34.010	-6.579
TENAN	-31.597	5.327	-5.931
RISK	-31.703	13.747	-2.306
TRADE	-31.563	11.596	-2.722
MANUF	2.942	4.141	0.710
UNEMP	-38.769	11.291	-3.434
REGN3	68.927	64.735	1.065
PDF_SP	1285.652	237.560	5.412
LGWAGEOP	-90.872	25.191	-3.607
LGPCRP	-7.931	14.867	-0.533
LGWAGESP	612.382	24.495	25.000
R^2	0.331		
Adjusted R^2	0.327		
*F test**	127		

stand error is calculated with bootstrap methiod with 500 replications

**Test IMR: H_0: PDF_OP=PDF_CRP=PDF_SP=0; critical value=7.81[x^2 (0.95,3)]*

Variable definitions are listed in Table 2.4 of Chapter 2.

Based on the estimation results, we can derive the price elasticity of CRP acres, labor supply for off-farm labor of the operator and the spouse. The elasticities calculated at the means of the data are listed in Table 6.7. [95] The CRP acre elasticity is estimated at 0.46, which means an increase of 0.46% acre enrolled in CRP corresponding to 1% increase in CRP per acre payment. The off-farm labor supply elasticity of the operator and the spouse are estimated as 0.33 and 0.36, respectively.

[95] The formula to calculate the elasticity follows the approach of Su and Yen (2000).

Our result suggests that the spouse is more responsive to changes in the marginal returns to labor. This finding is consistent with the finding of Abdulai and Delgado (1999) with the Northern Ghana farm household. The cross-wage elasticity of operator's wage on hours worked off the farm by the spouse and the spouse's wage on hours worked off the farm of the operator are -0.05 and -0.02, respectively. These finding suggest the slight cross-wage effect between spouse and operator albeit they are statistically significant. The off-farm wage increases 1% will increase the CRP acre enrollment by 0.03%. This is consistent with our expectation, since increasing off-farm wage of the operator will increase the hours worked off the farm, and thus reduce the farm labor hours. Given the hours worked on the farm decrease, it is likely to see less cropland in production.

Table 6.7: Price Elasticity Estimation

Variable	Coefficient	Std	b/Std	P_Value
	Hour_OP Response			
WAGE_OP	0.33	0.01	31.40	0.00
PAYMENT_CRP	0.01	0.01	1.12	0.13
WAGE_SP	-0.02	0.01	-2.02	0.02
	Acreage_CRP Response			
WAGE_OP	0.025	0.018	1.440	0.075
PAYMENT_CRP	0.458	0.036	12.577	0.000
WAGE_SP	0.001	0.019	0.054	0.479
	Hour_SP Response			
WAGE_OP	-0.053	0.009	-5.738	0.000
PAYMENT_CRP	-0.005	0.010	-0.446	0.328
WAGE_SP	0.359	0.011	32.195	0.000

***standard error is calculated by delta method based on the sample mean*

Concluding Remarks

This chapter focuses on the extension of the two decision case by considering the interrelationship between CRP participation, off-farm labor supply decision of the operator and the spouse of the farm household. Following the two stage approach proposed by Heckman (1979), we first analyze the decision making process of the farm household toward these three decisions by applying the trivariate probit model and the sequential decision model we propose. Under the joint decision framework, we find the positive and significant correlation between these three decisions, especially the higher correlation between off-farm work decisions of the operator and the spouse. When the sequential decision is assumed, it is more likely that the off-farm decision of the operator is considered prior to CRP decision and the spouse's decision working off the farm. However, the sequential decision model suffers from the IIA assumption imposed on the multinomial logit model, and is rejected by our data. As such, our result supports the hypothesis that that these three decisions are more appropriately described as the joint decision rather than sequential. They are also not independent decisions.

Given the joint decision process, we also analyze the CRP acre enrollment, hours worked off the farm by the operator and the spouse. Our result provides a positive evidence of the self-selection problem. We also find a positive price elasticity of the CRP acre response, hours worked off the farm of the operator and the spouse, although none of them is greater than one. The cross-price effects of these three decisions are very small, but statistically significant. Generally, increasing the off-farm wage of the operator will increase the acres enrolled in CRP.

CHAPTER SEVEN

SUMMARY AND CONCLUSIONS

In order to quantify the effects of recent changes in farm policy on the decisions of farm households, we focus on three participation decisions: Conservation Reserve Program participation and the off-farm work opportunities of the farm family. All of these are important sources of farm household income. The overall purpose of this research is to analyze the relationship of these three participation behavior of farm households. Specific objectives are given: 1) to identify factors related to decisions to participate in CRP; 2) to identify the extent to which off-farm labor decisions of the farm family members are related to CRP participation: are these two decisions determined jointly, sequentially or independently? 3) to identify the factors that determine the extent of CRP participations and off farm work as measured by the acreage commitment to CRP and off-farm hours worked; and 4) to quantify the effect of these participation decisions on the farm productivity and technical and scale efficiencies.

We motivate the study by developing a rather complex agricultural household production model. There are three major components to the empirical analysis, each involving a more complex discrete choice structure. The empirical analysis is based on data from the 2001 Agricultural Resource Management Survey (ARMS) from the US Department of Agriculture. This is the annual national survey of farm households that contains information about both farm business and farm household characteristics.

The theoretical framework is based on agricultural household models by incorporating price and production risk and technical efficiency as well as the environmental factors. The framework for farm households includes: Conservation Reserve Program and off-farm work opportunities and the possible receipt of decoupled payments. The finding of the theoretical analysis can be summarized as follows: price variability, the risk attitude of farm households toward price and production risk, technical efficiency, policy variables and the environmental characteristics jointly determine farm households' optimal choices. The CRP acres and off-farm hours tend to increase with the variability of prices and production, or when production is less technical efficient. However, because of the correlation between price and production risk the effect on CRP acres and off-farm hours remain undetermined. Another interesting finding from the theory relates to the policy implication of decoupled payments. Specifically, the effects of decoupled payments on the CRP acres and off-farm hours do not vanish if the risk attitude of the farm household exhibits constant absolute risk aversion (CARA). Moreover, if the environmental value to the farm household of CRP is ignored or is small, CRP acreage and off-farm work decrease, and farm work increase with higher decoupled payments. If risk preferences are CARA, increasing decoupled payments results in more CRP acreage.

To study the decision making processes of farm households and the factors determining the CRP acres and off-farm hours and the impact of these decisions on farm productivity, we use the theoretical framework to form three econometric models in the empirical analysis. Each of the models is based on the generalized sample selection model framework and estimated with a two-stage approach.

In the first econometric model, we focus on the CRP participation decision and its impact on farm productivity and technical efficiency. In contrast to previous literature, we consider the CRP decision as a sequential decision process: the farm household decides whether or not to participate in CRP as the first stage decision. Given the choice of CRP participation, the next decision is whether to enroll the entire farm or only part of it in CRP. Our empirical results show the importance of considering these two choices as sequential, but not two independent decisions. To avoid the endogeneity between per-acre CRP price acreages, we use an instrumental variable approach by estimating the per-acre CRP price equation first and then calculate the predicted price as the instrument of the CRP acre equation. To analyze the economic impact on farm productivity of the sequential CRP participation decision, we utilize a two-stage-method-of-moment approach to estimate the technical efficiency within groups based on the stochastic production frontier framework. This estimation provides the consistent estimates of the technical efficiency along with the sequential CRP choice structure. Furthermore, we compare the different performance of CRP participation decisions in terms of technical and scale efficiency, and production frontier difference by utilizing the Malmquist total factor productivity (TFP) Index.

The emphasis of the second econometric model is on two decisions of the farm household: CRP participation and the off-farm work decision by the farm operator. The context of the empirical analysis can be categorized in two parts. In the first part, we test three different decision making hypotheses for these two decisions: are they *joint, sequential or independent*? To avoid model misspecification, we estimate the two potential econometric models for both joint and sequential decisions. Under the joint decision hypothesis, we model the CRP participation and the off-farm work decision as a bivariate probit and a multinomial logit model; the nested multinomial logit and a new proposed sequential bivariate probit model are utilized to estimate the sequential decision hypothesis. The performance of these models is compared based on two non-nested tests: likelihood dominance criterion (LDC) and Vuong's test. Our empirical results promote the joint decision structure as an appropriate decision making process. Furthermore, the performance of the bivariate probit model dominates the multinomial logit model. To validate the empirical specification of the bivariate probit model, we test to see if other choices included in the models can be viewed as exogenous. The tests are based on Vella (1993) and Smith and Blundell (1986)'s methods. Our empirical results are encouraging since we reject the hypothesis that other variables are endogenous to these two decisions of interest. Similar to the CRP choice, we focus on the CRP acres response and off-farm hours of the operator in the second stage analysis, and compare the impact on farm productivity and technical efficiency. The approach we utilized here is similar to the one we have discussed in the sequential CRP model.

In the final econometric model, we extend our analysis by incorporating the spouse's decision for off-farm work along with these two other choices. Similar to the two-choice case, we propose two econometrics models for joint and sequential decisions, respectively. The trivariate probit model is specified as the joint decision model, and a new model combining the strength of binary probit and multinomial logit model is specified as the sequential decision model. Our empirical results suggest that the three-decision model is more appropriate than a sequential choice decision. That is, CRP participation and off-farm work decisions of the farm household are joint, rather than sequential decisions. Due to the difficulty in analyzing the CRP acres, off-farm hours of the operator and spouse based on the sample selection framework, we focus on the entire sample for the second stage analysis to derive the consistent estimates.

Model Comparison

Each of these three econometric models in this study has its own strengths. It is difficult to propose a generalized model incorporating all of the specialties of each model, since there is always a trade-off between computational demands and the model generalization. This is the reason that we proposed three different econometric models and estimate them in three different sections. Focusing on the CRP choice model, treating off-farm decision of the farm household as exogenous, we are able to explore the potential of a sequential CRP participation where we distinguish between enrolling all or only part of the farm in CRP. In so doing, we could compare farm productivity of non-participants with that of only partial CRP farm participants. Since whole CRP farm participants are no longer produce farm outputs, they must be excluded from any farm productivity comparisons.

Focusing on two decisions of the farm household toward CRP and operator's work off the farm, we are able to examine the decision making process in greater detail and explore information in terms of the various decision making process, along with the impact on farm productivity. When the model is extended to incorporate the spouse's work off the farm decision, an alternative empirical strategy is necessary due to the computational difficulty. The primary conclusion derived from our analysis suggests that the off-farm working decision of the farm family and the CRP participation are jointly determined, which is validated in the two-choice and three-choice estimations. These results all seem to support a joint decision structure, but since the analysis is based on cross sectional data, it is difficult to know how the results might have changed had we had access to panel data containing information about the actual timing of these two decisions. What is perhaps clear from the analysis is that these two decisions are not made independently, a finding that should have important policy significance.

The effects of the factors determining the participation decisions of these three choice models are quite robust across models. As such, we might promote the usage of the two-choice model for empirical analysis since this model allows us to discuss not only the decision making process in great detail, but also implement the second stage analysis and examine farm productivity in a comprehensive fashion. The primary difficulty to analyze the farm productivity of the three-choice model is related to the specification of the correction terms for self-selection problem (Inverse Mills Ratio) explicitly. With the case where there are more than two choices of the farm households involved, the algebra for deriving Inverse Mills Ratio requires to calculate the *conditional* expected value and variance of the multivariate truncation distribution, which is computational cumbersome. Without these, we are not able to focus on the group estimations and compare the performance in terms of acreage response or productivity between groups. Although focusing on the *unconditional* expected value and variance of the multivariate truncation helps for analyzing the second stage and productivity, it explores less information than the case if each participation group is focused and analyzed. To our best knowledge, the methodology to estimate the performance of each group within the sample selection framework had not been proposed in the literature.

Primary Finding of the Empirical Analysis

Regardless of the model specification, several factors determine the participation decisions of CRP and off-farm jobs of farm households. CRP participation depends generally on some characteristics of the farm, the farm operator, land quality, and the circumstances in the local economy. There are also some differences in participation by major ERS production region. One interesting finding is the CRP acreage response in terms of CRP per-acre payment. We do find the positive evidence of CRP acre response but it decreases with the increase of low land quality index. If the proportion of the low land quality is high, the CRP acreage response to per-acre price might be negative. This result helps to explain the contradiction of the previous studies in terms of the CRP acreage response. Environmental factors play a role of CRP participation. One obvious example is the EBI score. That farm households located in areas where the EBI scores for land currently enrolled are high are more likely to participate in CRP, since in areas where the EBI scores were high, farmers might well expect to have higher bids accepted.

The empirical evidence of risk attitude of the farm household to the CRP participation is consistent to our theory, even though the measure of risk attitude with ARMS data is rather ad hoc. As aversion to risk increases, the likelihood of participation in a program where payments are certain, such as CRP, will increase. Our theory is also consistent with the fact that decoupled payments reduce the likelihood of CRP participation. Finally, since commodity program related loan deficiency payments and decoupled payments reduce farm income variability, these payments also reduce risk averse farmers' concerns for allocating farm resources to programs, such as CRP.

As expected, the decision of the farm operator to engage in off-farm work also depends on the characteristics of the farm, the farm operator, and the circumstances in the local economy. Our results confirm the fact that older farmers are more likely to work off the farm; the operator's education has a positive effect on the probability of participation in off-farm work, the years of experience on the farm has a negative effect that increases at an increasing rate. Farm operators raised on farms are also less likely to work off the farm. Since returns to off-farm labor are likely to less variable than farm returns, the indication that the likelihood of off-farm work participation is lower for farm operators willing to accept more risk is consistent with the theory of risk averse behavior.

Another interesting and unique finding of this study is the qualification of the impact on farm productivity of CRP participation and the off-farm work decision of the farm operator. We find that participating in CRP appears to lower the technical efficiency but raises the scale efficiency. We also find that participating in off-farm work increases technical efficiency and scale efficiency. These results may imply that efficiency is more adversely affected when land is withdrawn from production without also withdrawn labor. The reverse is not true.

Some Policy Lessons

Several policy implications related to CRP policy design are found in this study. First, targeting at the EBI score is important since EBI determines not only the CRP participation decision but also the acreage enrolled in CRP. The farms in the area with higher EBI score are likely to participate in CRP and enroll more acreage in CRP. Second, we also find that the positive and statistically significant upward sloping CRP acreage supply functions. However, the acreage response to per-acre payment falls and can become negative in acres where there is a high proportion of low quality land. These results seem interesting since these are consistent with the belief by some that per-acre payments have been raised to attract high quality land in some areas, but are also consistent with farmers' submitting lower bids to ensure that bids of low quality are accepted. Finally, we find evidence of a positive relationship between CRP and the off-farm work decisions of the farm household and it is reinforced by the positive effects of off-farm wage on CRP acreage. Increasing the opportunities for the off-farm work seems to increase not only the probabilities of participation in CRP, but also the acres enrolled. Due to the nature of the joint decision between CRP participation and off-farm work, the design of CRP policy can't ignore the factors that might affect decisions to work off the farm by farm households.

Several policy implications also might be inferred from our study in terms of decoupled payments. Promoting decoupled payments program, as a substitute for conventional commodity programs, seems to be the direction of agricultural policy designs in the future. The first policy implication comes from the importance of decoupled payments on both CRP participation and off-farm work decisions by farm households. Increasing decoupled payments would generally decrease the probability for CRP participation and off-farm work decisions.

Finally, since participation in both CRP and off-farm work affects the allocation of farm household resources between farm and non-farm economic activities, there are important effects on the technical and scale efficiencies of farm production. However, the implications of these policies that affect the choices can be fully understood only by comparing their effects on the efficiency of total farm household production when compared with farm productivity. Through this extended analysis, it will be possible to determine the effects of these decisions on overall farm household income and well-being. It is in this area that further research should be directed.

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